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Skills mismatch measurement
in ETF partner countries

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EXECUTIVE SUMMARY

This report focuses on a critical concern for the ETF's partner countries and other countries around the world. Skills mismatch is recognised as a major challenge by policy makers, practitioners and social partners, as it is often associated with dynamic social and economic contexts such as restructuring processes, changing trade patterns, technological progress, demographic change or negative social aspects (e.g. informality, long-term unemployment, inactivity).

Skills mismatch is a complex phenomenon, expressed in different types and dimensions of labour market friction. A combination of indicators and analyses of results from different methods is required to measure and understand the magnitude and interrelatedness of the different forms of skills mismatch. However, the data sources needed to measure and predict the different forms of skills mismatch are not always readily available in all ETF partner countries, and only a few international studies have included ETF partner countries. An expanded set of indicators needs to be calculated and analysed from multiple angles. The aim of the project on which this report is based was to assess the suitability of selected skills mismatch indicators for practical implementation in ETF partner countries.

In 2017, the ETF launched a project on skills mismatch measurement in the ETF partner countries. Its objective was twofold: to identify available data sources and to test a series of indicators capable of capturing various angles and implications of skills mismatches. This project built on previous conceptual work conducted by the ETF on skills mismatch measurement and applied research carried out in 2011 (ETF, 2012).

Using a combination of international and local expertise, and in consultation with national stakeholders, the ETF project aimed to review the suitability of the indicators and methods for measuring the incidence of mismatch. This included testing a methodological approach that was adapted to the context of selected countries (transition or developing countries), while ensuring, as much as possible, comparability across ETF partner countries and with European or international research on similar topics (e.g. Cedefop, OECD, ILO).

Seven ETF partner countries were included in the two phases of the project (2017 and 2018): Egypt, Georgia, Moldova, Montenegro, Morocco, North Macedonia and Serbia. Country-specific analyses were developed to contextualise the skills mismatch measurement for each country and to analyse the insights gained from each of the indicators that were calculated.

This report complements the country analyses and findings and highlights commonalities across countries. Moreover, the report delves into methodological aspects with a view to possibly replicating the skills mismatch measurement and analysis in other ETF partner countries, and embedding this analytical capacity in national policy development.

The usefulness of the term 'skills mismatch' has been criticised by the ILO (2017) as an overly generic umbrella term that hides different forms of mismatch, each with different manifestations, requiring different measurement methods and different policy responses. The term is used in relation to vertical and horizontal mismatch, skills gaps, skills shortages, and skills obsolescence. Some forms of skills mismatch have been the subject of extensive research initiatives, as demonstrated by the large number of published analyses on vertical mismatch (over-education, under-education, and to a lesser extent, also over-skilling). Other forms of mismatch, such as horizontal mismatch, skills shortages, skills gaps and skills obsolescence are less represented in the literature. Some concepts of skills mismatch have drawbacks and some measures are poorly correlated.

The available data and the nature of the indicators used have both strengths and weaknesses. Skills mismatch is mostly measured by proxy in this ETF project, with data on education and occupation used as proxies of skills. Moreover, the nature of the methodologies and indicators used determines the relative limitations of their predictions. For example, the proportion of unemployed people versus employed people indicates the *direction* of the mismatch (i.e. the deficit or surplus of specific education levels) and generalises at the macro level. Other indicators, such as the coefficient of variation and the variance of relative rates, show the *magnitude* of mismatch and generalise at the macro level. The Beveridge curve measures the relationship between unemployment and vacancy rates, but might be limited for most ETF partner countries.

A deeper knowledge of the nature and incidence of skills mismatch, including good contextualisation (e.g. socio-economic aspects, labour regulations, job matching services), can help countries to better target their efforts to match supply and demand. This can be done through a wider set of policies and measures covering education, training, employment and other policy interventions directed at better utilisation of skills and labour resources. Such an analytical exercise may also help institutions and partners to assess the effectiveness of their skills policies.

In describing and interpreting the indicators and, where possible also how they are interrelated, we provide information about the methodology and data sources used to measure skills mismatch. We also hope to help clarify the incidence of skills mismatch and provide some predictive insights into areas where mismatches might occur in the labour market. Anyone who generates, interprets or uses labour market information or is involved in labour market and/or education policy may be interested in understanding the various ways in which the labour market and skills can be analysed. Finally, proposals on how to further develop indicators, data infrastructure or skills and labour market analysis are provided for the various countries and the ETF.

Chapter 1 introduces the background to this initiative, the methodological anchors and previous work done by the ETF on the subject. Chapter 2 delves into general methodological insights on the definition, measurement and interpretation of skills mismatches. Chapter 3 includes the methods chosen and the steps implemented in the ETF project to collect and prepare the datasets for selected countries. The reasoning behind selecting a number of key mismatch indicators is also discussed in this chapter, as one of the main principles guiding the research was to ensure, as far as possible, comparability of calculations and findings across countries. Using a cross-country comparative analysis, Chapter 4 focuses on the actual findings of the mismatch measurement in the selected partner countries. The findings include calculation results, interpretation, possible caveats and data limitations. The final chapter discusses the lessons learned in the implementation of the methodology using national data, draws conclusions and recommends possible avenues for the partner countries and the ETF to replicate and further analyse the incidence and nature of skills mismatches.

1. INTRODUCTION

Insights into the forms, incidence and interrelatedness of skills mismatches allow governments, social partners, industry and other stakeholders to devise ways to address the causes of such imbalances and improve matching between skills supply and demand. This can usually be done at several levels as acknowledged in the renewed Skills Agenda for Europe (2016)[1]: (i) improve the quality and relevance of skills formation; (ii) make skills more visible and comparable; and (iii) improve skills intelligence and information for better career choices.

Over the years, the ETF has worked on implementing and supporting skills intelligence and policies. It has also worked on projects to identify and overcome skills mismatches. The position paper 'Anticipating and matching demand and supply of skills in ETF partner countries' (ETF, 2012a) described the analytical and methodological background, which served as a framework and background to subsequent ETF activities. In partnership with the European Centre for the Development of Vocational Training (Cedefop) and the International Labour Organisation (ILO), the ETF developed six methodological guides on skills anticipation and matching. This was a further practical step in assisting national governments with the implementation of adequate measures to identify skills trends and overcome skills mismatches (ETF, Cedefop, ILO 2015, 2016a-d, 2017). The ETF's methodological note *Measuring mismatch in ETF partner countries* (ETF, 2012b) summed up the conceptual and methodological underpinnings of our in-house research in this domain. Based on this methodological note on indicators of skills mismatch, piloted in 2012 with data from seven partner countries[2], an initial skills mismatch measurement exercise was drawn up, upon which the current project will build[3]. The ETF's methodological note focuses on quantitative methods, explains theoretical differences between methodologies, discusses concepts and terms and presents a concrete case study using data from Turkey. A comparative cross-country analysis of the indicators completed this initial research[4].

A broad definition of skills mismatch is used in this project. It encompasses gaps and imbalances in skills in the labour market that could be identified as over- or under-qualification, labour market shortages or surpluses by qualification or skill, hiring difficulties, underemployment or unemployment by qualification or skill. Different groups within the labour force may be affected, and different sectors or occupations may have more pronounced problems.

The consequences of these mismatches can be manifold. At an individual level, they range from attrition due to employment in occupations that are not well aligned with the skills of the worker, all the way to withdrawal from the labour market as a result of discouragement, leading to inactivity. If skills are acquired but not used and updated or maintained, this can lead to skills obsolescence that diminishes the actively available set of skills in a person's human capital.

Labour market research has analysed skills mismatches in labour markets from many different angles, using specific groups or times in the careers of a worker (e.g. school-to-work transitions), the relationship between formal qualifications and job requirements (e.g. over- and under-qualification), and the relationship between the use and non-use of skills, as outlined in the skills obsolescence literature. New data on skills obtained from large-scale OECD studies on school achievement (PISA) and adult skills (PIAAC) has allowed us to examine the link between skills, qualifications and occupations. While interlinked employer-employee surveys have allowed us to examine the (perceived) underutilisation of skills in workplaces.

The aforementioned methodological note published by the ETF (2012) concludes that no single methodology and indicator can capture the diversity of key aspects of skills mismatch. A combination of methods is recommended to help countries explore as many dimensions as possible, taking into account data availability and analytical capacities, as well as country-specific aspects and important issues relating to skills and employment.

Just as the use of a range of indicators based on pre-existing data was found to be cost-effective for Turkey in the ETF research conducted in 2012, it makes sense to analyse the availability of data more broadly. In addition, the aspect of comparability across countries can be examined and used to identify national imbalances in labour market analyses of ETF partner countries.

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1 See http://ec.europa.eu/social/main.jsp?catId=1223

2 Croatia, Montenegro, Serbia, Turkey, Moldova, Ukraine and Egypt

3 See www.etf.europa.eu/web.nsf/pages/Measuring_mismatch_methodological_note

4 See www.lse.ac.uk/europeanInstitute/research/LSEE/Events/PDF_Files/2012_Belgrade_Workshop/Bartlett-Johansen-Gatelli.pdf

2. METHODOLOGICAL OVERVIEW OF SKILLS MISMATCH MEASUREMENT

The body of knowledge and recommendations summed up in the ETF methodological note (ETF, 2012b), as well as other important studies carried out on skills mismatch by the European Commission's Joint Research Centre (JRC, 2014), Cedefop (2015), the European Commission (2015), Eurostat (2016), Handley et al. (2017) and McGuiness et al. (2017) represent the essential conceptual and methodological starting point.

While labour market imbalances generally refer to a difference between demand and supply, mismatch concentrates on a certain dimension of such imbalances. Usually the focus is on the skill or qualification level. A distinction is often made between the types of mismatch. There may be a mismatch in numbers, i.e. at the quantitative level. For example, there may be an overall shortage of workers compared to the number required. The mismatch could also manifest itself at a purely qualitative (content) level. The latter case would imply that there is sufficient supply in terms of headcount, but that the supply does not provide a good match in terms of skills demanded versus skills available in the workforce.

2.1 Types of skills mismatch

The types of skills mismatch as defined in Quintini (2011) and Cedefop (2015) combine the element of qualification versus skills with the quantitative versus qualitative mismatch argument. While qualifications are usually the only measure available in labour force surveys, it can be misleading to use them as proxies for skills. Qualifications can cover a wide variety of skills – in terms of level, quality and combinations of skills. While skills and qualifications can be attributed to similar traits and life choices (education, career), it is by no means necessary that the underlying correlation between the two also translates in terms of skill and qualification mismatch. Often a mismatch in education is not reflected in a mismatch in skills, or a mismatch in skills is not reflected in a mismatch in qualifications, as the JRC (2014) finds. Each of these situations identify a different underlying problem; they warrant a different approach if the mismatch is deemed to be important enough. In specifically analysing the World Bank's STEP programme, which is geared towards low- and middle-income countries, Handley et al. (2017) show that even in lower-income contexts, many workers are over-qualified for their jobs and unable to take full advantage of their skills.

In combined employer-employee surveys, as reported in Cedefop (2015) and McGuiness et al. (2017) for example, identified differences between skills and qualifications mismatch can also result from perceived underutilisation of skills. The use of certain skills often also depends on the full combination of available skills[5]. Thus, some employment relationships seem to underutilise skills especially if the full set of skills is not measured or identified.

Important findings from the Cedefop study (2015) reveal that '[c]loser stakeholder collaboration and policy action is needed in the EU to generate not only more skills but also, crucially, better jobs for better-matched skills'. The study also finds that there are a multitude of reasons and underlying factors that generate skills mismatch at an individual level. Thus, identifying mismatch, preferably for more detailed groups and using a variety of indicators, will facilitate a better understanding of the types of mismatch and its potential causes. Only then will policy makers and stakeholders be able to discuss implications in a useful manner.

2.2 Dimensions of skills mismatch

The dimension of skills mismatch at the micro level is a matter of *level*. In other words, a person may have the right skills for a specific task or occupation, but the level of the skill is lower than what would usually be required for the specific occupation or task. This is usually referred to as vertical mismatch, or over- and under-education and/or over- and under-skilling. There can be several reasons for a vertical skills mismatch. Generally, it happens at the level of the match between a firm and a worker if no suitable employee is available to hire at the time of an existing vacancy (and the person hired is under-qualified or under-skilled), or, if, on the other hand, the person hired is over-qualified.

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5 For a theoretical discussion of bundles of skills and the utilisation of individual skills in jobs, see also Lazear's skill weights approach, as described in Lazear (2009).

A horizontal mismatch occurs when the qualification level is sufficient, but the type or field of qualification does not adequately match. This is more common if a person is working in a related field, where for example sufficient numbers of computer programmers with a qualification in computer programming are not available, but individuals with qualifications in related fields are available, e.g. mathematicians, engineers. However, a horizontal mismatch could also imply a much bigger discrepancy between fields required and fields hired, e.g. a philosophy graduate is hired as a computer programmer. The more detailed job requirements can be measured in terms of skills or qualifications, the more likely that (some) horizontal mismatch is found. The corollary is also that the less detailed the data is, the less likely it is to identify a horizontal mismatch, even if it exists.

Table 2.1 Main types and dimensions of skills mismatches

Type	Dimension	Definition	Data source/type of measurement
Over-education (over-qualification)	Vertical	Worker's level of education (qualification) exceeds the required level for the job (occupation)	Labour force survey (LFS) Administrative sources (e.g. registries of labour contracts, social insurance, tax) Transition studies Employers' surveys Surveys of self-reported usage of qualifications and skills (e.g. tracer studies, workers' surveys, PIAAC)
Under-education (under-qualification)	Vertical	Worker's education (qualification) level is lower than the required level for the job (occupation)	As above
Over-skilled[6]	Vertical	Level of skills (usually broadly defined as knowledge, competency, abilities) exceeds the job's requirements	Transition studies Employers' surveys Surveys of self-reported usage of qualifications and skills (e.g. tracer studies, workers' surveys, PIAAC, PISA)
Under-skilled	Vertical	Skill level is below job's requirements	As above
Field of education to occupation mismatch	Horizontal	Field of study does not match the occupational area of the job	LFS Administrative sources (e.g. registries of labour contracts, social insurance, tax) Transition studies Employers' surveys Surveys of self-reported usage of qualifications and skills (e.g. tracer studies, workers' surveys, PIAAC)

Continued

[6] Over-skilling often coexists with vertically matched education-occupation levels, namely the worker has the required educational attainment level but not the full set of skills required to exercise that occupation.

Table 2.1 Main types and dimensions of skills mismatches (cont.)

Type	Dimension	Definition	Data source/type of measurement
Skills shortage (or over-supply)	Quantitative	Certain skills are in short supply (or over-supply), typically expressed as an insufficient number of job seekers to fill the available jobs (or vice versa)	LFS Vacancy monitoring
Skills gap	Qualitative	Level of available skills of workers is lower than the required level to perform the job (often associated with changing economic context or changes in technology)	Transition studies Employers' surveys Surveys of self-reported usage of qualifications and skills (e.g. tracer studies, workers' surveys, PIAAC)

Sources: Adapted from ETF/Cedefop/ILO (2015, 2016a–d, 2017)

2.3 Measuring skills mismatch

Skills mismatch discussions are often obscured by the fuzziness of the general term. The various concepts and elements included under the umbrella term 'skills mismatch' are measured differently. Various actors will see outcomes quite differently, and indicators do not necessarily coincide, depending on the concept of skills mismatch they measure or the way the skill or mismatch is proxied.

One way to measure skills is to use qualifications[7], thus identifying a qualifications mismatch. The level of aggregation will determine how useful the identification of a skills mismatch at the available level of detail will be in answering certain questions. A macroeconomic skills mismatch, using unemployment or vacancies according to broad qualification levels for example, provides a good insight into the general problem of mismatch in the labour market and can be helpful in making broad policy decisions.

Analysing or steering specific education decisions, or more detailed sector-level stakeholder discussions, will require much higher levels of detail. Identifying horizontal mismatch or a more detailed analysis of vertical mismatch requires matching detailed qualifications with occupations and their requirements.

This can often be done at a broad level by comparing demand by occupation and its implied qualification requirement, as part of the ISCO classification, with the matched supply in terms of qualification attainment. Eurostat (2016) calls this the 'indirect' approach to measuring skills mismatch.

The direct approach, as indicated by the name, attempts to directly measure the status of the skill of individual job holders and those skills required within qualifications. Any skills mismatch can then be seen when the (revealed) skills requirement and the skills of individuals are compared, e.g. measured as part of a survey of skills such as the OECD's PIAAC or PISA surveys, which enable a direct assessment of literacy or numeracy skills, for example, and allow individuals to self-report for other generic skills (e.g. teamwork skills).

[7] Formal qualifications proxied by diplomas (i.e. the successful attainment of a certain level of education).

If skills are not measured directly, but are self-assessed by either the worker or the firm, it is a subjective, self-reported approach. This is commonly done in tracer studies of graduates, but also in many employer-employee surveys.

It is important in this context to understand the definition of normal skills requirement, i.e. what is the required level that determines over- and under-qualification? At occupation level, it can sometimes be determined by specific requirements in qualifications that lead directly to the occupation to be analysed. Hence, a person with a qualification below this level is under-qualified. However, in many cases there is no general one-to-one relationship between occupation and required qualification level as there are a range of qualification levels and career paths leading towards specific positions or occupations. Higher qualifications usually shorten the paths towards occupations, fulfilling implicit skill requirements. On the other hand, many years of experience can also fulfil the skills requirements for specific positions – even if the person is technically less qualified, they may be able to compensate for this by the experience and informal learning they have gained from working. This means that indicators measuring vertical mismatch are prone to giving fuzzy results. Not all mismatches are necessarily bad or economically harmful.

As discussed above, the more detailed job requirements can be measured in terms of skills or qualifications, the more likely it is that (some) horizontal mismatch can be found. Horizontal mismatch seems to occur more in occupations that are broader in terms of skills requirements or the tasks performed but are less likely in occupations that have (legal) requirements, such as the medical profession or the teaching profession. However, while legal requirements might mean that no horizontal mismatch is observed, this does not necessarily mean that a problem does not exist. Because of legal obligations, vacancies may not be filled with similarly qualified persons, thus increasing potential shortages if they exist. They will, however, show up in indicators of shortage (e.g. vacancies, vacancy duration, occupations with hiring difficulties), rather than in indicators of skills mismatch.

3. METHODOLOGICAL CONSIDERATIONS AND DATA SITUATION IN SELECTED PARTNER COUNTRIES

In the subsequent sections we will present the methodological approach and implementation of the research project in the seven pilot countries, including an overview of available sources of data and eventual limitations of such sources. An explanation of the choices made in relation to skills mismatch indicators is also provided.

The first section discusses the mapping of available data in all countries. It also covers the indicators, which are based mainly on micro-level, labour market data, most likely labour force surveys, which are available in most countries. In addition, many countries have access to additional data from various sources, which is collected at varying frequencies. We will discuss potential additional indicators and provide some examples from the pilot countries. In the comparative analysis, however, we will restrict ourselves to the indicators that are likely to be available for all countries, albeit in various degrees of disaggregation.

Each indicator covers a certain aspect of skills mismatch or labour market mismatch. Depending on a country's institutions, data collection method or the relevant policy issues, one set of indicators might be more useful than others. Where possible, we will comment on that in this chapter but also in the comparative analysis. Many indicators also overlap or show the same aspect of mismatch to varying degrees. This is intentional but also helps to get a better picture of the overall mismatch in the labour market.

3.1 Mapping of data sources: data availability and reliability

The aim of the project was to identify the most regular, reliable and affordable solutions to calculate skills mismatch at country level. The second guiding principle was to use comparable sources of data across the countries to allow the ETF and other interested actors to re-run or replicate the exercise in other countries or at different points in time (e.g. every two or three years).

During the inception phase of the project, the international and national experts, together with the ETF team, analysed various options based on a variety of factors including country background and data availability. They also analysed the usefulness of different indicators to capture skills mismatches. As outlined in the next section, labour force surveys proved to be the most reliable sources of information as they are established and regular practice in the selected countries and in the majority of ETF partner countries.

The data for the calculation of the mismatch indicators was collected by national experts. In order to formalise and streamline the process, a data collection template was generated following a three-step procedure.

1. In the first step, the national experts provided information on the national availability of required basic and in-depth variables using a questionnaire. This included the possibility of accessing data through microdata (which was eventually the case for Egypt and Georgia), or through aggregate data tables in the remaining countries. It also contained information on national classifications of educational attainment levels, occupations, data quality and other variables of interest for mismatch calculation.
2. In the second step, the data collection template was adapted to the national circumstances by the international expert. This template was sent to the national experts to transfer the data into it. In cases where microdata was available and where it was permissible to transfer this data into the template, it was also transferred. In other cases, the more elaborate template was used to provide the necessary data tables.
3. The final step involved calculating the indicators based on the microdata or the aggregated tables provided by the national experts.

In order to be able to compare some of the indicators, the project required the national experts to obtain comparable data which included 2016 as a common base year in all countries. To examine national dynamics, additional years were requested around the base year.

The main data source in all countries was the LFS data. Table 3.1 provides an overview of the data in the seven pilot countries that was mainly used for this report.

Table 3.1 National LFS data availability

	Egypt	Georgia	Moldova	Montenegro	Morocco	North Macedonia	Serbia
Type	Microdata	Microdata	Aggregate data	Aggregate data	Aggregate data	Aggregate data	Aggregate data
Years available	2008–16	2009–16	2012–17	2014–17	2012–16	2012–17	2014–16
(Technical) data issues	CAPMAS data harmonised by the Economic Research Forum (ERF). In some cases, the variable names used from 2008 to 2014 (provided by expert) differ from those used in the 2015, 2016 dataset (received directly from the ERF)	Re-calculation of indicators was necessary due to a revision of microdata by Geostat (National Statistics Office of Georgia)	Small cell size, limitations and less flexibility as data had to be aggregated by the national expert or the relevant national institution	Small cell size, limitations and less flexibility as data had to be aggregated by the national expert or the relevant national institution	Limitations and less flexibility as data had to be aggregated by the national expert; not all variables were available, limiting comparability	Small cell size, VET education levels not available, limitations and less flexibility as data had to be aggregated by the national expert or the relevant national institution	Limitations and less flexibility as data had to be aggregated by the national expert or the relevant national institution

Most LFS data variables for Morocco are available for the years 2012 to 2016. This data was aggregated and collected by the national expert. Although some information was collected in the LFS, it was not made available to the national expert. For example, no data on employed people or inactive people by educational attainment level and age group could be provided. Also, some variables were available for the 15 to 59 age group, while others only for the 15+ age group. There were also some inconsistencies regarding the breakdown of data by age group and educational attainment level. This made it difficult to ensure comparability of indicators within Morocco as well as across countries.

Egyptian LFS microdata was available for the years 2008 to 2016. At the time of calculation, datasets prepared by the Egyptian Economic Research Forum (ERF)[8], which are based on data collected by the Egyptian Central Agency for Public Mobilization and Statistics (CAPMAS), were available up to 2014. Only unprocessed CAPMAS LFS microdata was available for 2015. This meant that this dataset had to be prepared separately. After harmonisation, the CAPMAS dataset was merged with the ERF dataset. Data for 2016 was only available in Arabic and was therefore not used. The Egyptian LFS is sufficient to calculate most of the indicators used in this report except for the Beveridge curve as, typically for labour force surveys, no data on vacancies was collected.

LFS data for Georgia at the time of calculation was available for the years 2012 to 2016 and was made available as microdata. This allowed deeper analysis of the data and a direct calculation of the indicators. All datasets up to 2017 are available and are accessible online on the Geostat (National Statistics Office of Georgia) website. In 2017, a new, separate LFS was launched in Georgia. It contains a revised questionnaire and has a bigger sample size (around 6 000 households). More non-LFS-based data would have been useful in assessing more specialised skills mismatch measures. Since the school-to-work transition seems to be especially challenging in Georgia, a more structured and regular (in terms of frequency) practice of investigating the transition from school to work (such as transition surveys, tracer studies) would provide more detailed insights into the potential shortcomings of the education process in providing adequate and practical skills, or in providing an adequate number of graduates in particular fields.

LFS data for the years 2012 to 2017 was used for Moldova. Overall, reasonably comprehensive data relating to education, skills, employment and the economy is available. The country expert provided data for the project; the project team did not have direct access to microdata. Given the size of the country, analysing and calculating the data along several dimensions often exhausted the limits of the sample size. Moldova's national statistics office has been using the EU classification system for statistical data since 2014, allowing for easy comparison. Considering the importance of cross-border migration for work, further statistical data collection and work might help in analysing this specific aspect of the country's labour market.

LFS data for the years 2014 to 2017 was used for Montenegro. Most of the data requested was available. Since country's statistics office does not generally release microdata, the microdata was aggregated by the office's own employees based on detailed instructions from ETF experts. The main challenges included several problems with proposed breakdowns of age groups and educational levels, as these led to many inaccurate estimates. These issues resulted from the small overall sample, due to the small size of the country.

LFS data for the years 2012 to 2017 was used for North Macedonia. The data was compiled by the national expert using MakStat and Eurostat databases based on LFS data produced by the State Statistics Office (SSO), as direct access to microdata is limited. There were some limitations due to overall sample sizes. Some educational data in education-related publications was also obtained from the SSO; data was also obtained from the recently conducted Adult Education Survey. The SSO plans to conduct the survey every five years, which is in line with Eurostat recommendations. Data from the survey is also published on the SSO website in report and table form.

Serbian LFS data was available for the years 2014 to 2016 at the time of calculation. Although there were some minor comparability issues between

8 See www.erfdataportal.com/index.php/catalog/125

2014/15 and 2016 (different classification of field of education) and the data collection process required a comparatively high amount of coordination as microdata was only made available to the national expert, the Serbian LFS provided sufficient detail to analyse skills mismatch.

In addition to LFS data, an attempt was made to find further data sources that could feed into potential indicators. Additional data that was not LFS-based was also requested from the national experts. Table 3.2 shows the additional data that was available in the seven countries. Given that this data was not used consistently across countries, as it was not comparable or structurally collected, the data has been used as additional background information.

The main drawback of non-LFS data is that it is collected on an ad hoc basis or less frequently than LFS data. Even the most recent versions of such datasets are often quite dated.

For example, in the case of Egypt, ELMPS survey data, which is published by the Economic Research Forum, contains individual and household variables that are just as detailed as Egyptian LFS data and furthermore allow for longitudinal analysis. However, the latest round available is from 2012. In addition to some standard labour market variables like occupation and work contract information, the Higher Education Graduates Survey (2012), published by the Cairo Demographic Centre and the Economic Research Forum, contains information on topics like specific skills required in current job, self-assessed skill level and job satisfaction. The latter point to participants that experience skills mismatch. As in the case of the ELMPS survey data, this information is not quite up to date. Furthermore, it only applies to individuals with a higher level of education and therefore only to one side of the skills mismatch. The Survey of Young People in Egypt (SYPE, conducted in 2009 and 2014) is published by the Population Council. It focuses on younger people (aged between 10 and 42, 2014 survey) and contains detailed household-related questions. It also contains some relevant labour market variables and information on migration, which can be used to analyse skills mismatch.

In Serbia, two additional datasets were available in addition to the LFS. The first was the ILO's 2015 Serbian school-to-work transition survey. This is a very detailed survey, conducted among younger people aged between 15 and 29. It contains many standard relevant labour market variables (e.g. place of work, occupation, hours worked, work contract information, wage). It is also very detailed in relation to work experience and employment history as data on experience in up to 10 jobs is collected from each participant. There are also some variables that can be analysed to gather information on skills mismatch among the younger population, e.g. variables that record reasons for never attending school, problems in engaging with the labour market, a desire to change employment situation or the occupation that a person wishes to work in. The second dataset contains Serbian employers' survey data (2014, 2015, 2016). It contains very detailed information on occupations in demand, broken down by education level and specific knowledge (skills).

The ILO's school-to-work transition surveys, implemented in all selected countries (except Morocco), concentrate on the (school-to-work) experiences of young people aged between 15 and 29. They include information on the suitability of the individual's own skills or education level to the current job they are performing, as well as problems encountered in the current job that might indicate skills mismatch.

While data on demand (such as vacancies, skills needs as expressed by employers) is available for all countries, it is difficult to make cross-country comparisons as most sources are either administrative (regular monitoring of vacancies by the public employment services, PES) or survey-based (employers' survey) and largely reflect specific information needs and country context.

These additional datasets were used as background information only. They often provided very insightful and detailed information on a subset of the population or on a specific set of variables. Often the data-sets were only collected infrequently or on an ad hoc basis.

Given the limited availability of such data and the fact that we could not find general comparability across several countries, the project team did not include the data when calculating specific indicators. These datasets should, however, be seen as potential sources for further analysis and data collection at a national level.

Table 3.2 Additional (non-LFS) data

Egypt	Georgia	Moldova	Montenegro	Morocco	North Macedonia	Serbia
ELMPS panel survey, 1988, 1998, 2006, 2012 (Economic Research Forum) Higher Education Graduates Survey 2012 (Cairo Demographic Centre, Economic Research Forum) Survey of Young People in Egypt 2009, 2014 (Population Council) School-to-work transition survey 2012, 2014 (ILO)	STEP (employers' survey) 2012 (World Bank) Labour market demand survey (employers' survey) 2015 Georgia youth study 2016 (ACT) National youth survey 2017 (UNICEF)	ILO study on school-to-work transition (2016) PES vacancy monitoring (regular analyses of occupations in demand)	DGEAC study – From university to employment: higher education provision and labour market needs ILO study on labour market transitions of young women and men in Montenegro PES vacancy monitoring	Integration survey of vocational training recipients (2012, 2013 graduates) Prospective surveys on demand, run by the National Agency for Employment and Skills Promotion (ANAPEC)	DGEAC study – From university to employment: higher education provision and labour market needs Adult Education Survey (2016) ILO study on school-to-work transition (2015) PES vacancy monitoring	DGEAC study – From university to employment: higher education provision and labour market needs ILO school-to-work transition survey 2015 Employers' survey 2014, 2015, 2016 (PES)

3.2 Choice of indicators

As mentioned at the beginning of this chapter, the indicators are based on labour market data, which is likely to be available in most countries. Data that is collected by an LFS is available in most countries that have at least a basic statistical infrastructure to monitor the workings of the labour market. In addition, most labour force surveys follow the general model of taking a representative sample of the population and providing sufficient demographic, employment and education background to produce useful labour market information in terms of skills or education by level and type, employment by sector or occupation, age and gender. We use these breakdowns to calculate the main indicators.

Meaningful indicators should fulfil the criteria listed below.

- The data should be easily accessible.
- The underlying data should be reliable. This implies that there should not be huge changes in the indicator values from wave to wave of the underlying data. This requires the data to have a sufficient base of underlying values. If necessary, an indicator with less detail would suffice.
- The data should be updated regularly to prevent the indicator from becoming outdated.

Table 3.3 provides an overview of key indicators used in signalling mismatches. These indicators are based mostly on LFS data, which is widely available in all ETF partner countries.

Table 3.3 Mismatch indicators: definitions and interpretation

Indicator	Definition	Purpose	Data source(s)	Interpretation
Unemployment rate	U/(E+U)	Official unemployment rate Often a strict definition of unemployed (person searching for work within the past four weeks)	LFS	Higher unemployment rates show a mismatch between demand and supply.
Unemployed/ employed ratio	U/E	Like the unemployment rate Simpler to calculate Provides a direct interpretation of the ratio of employed to unemployed people	LFS	See above. Note also that the different groups might exhibit quite different ratios. Here, youth unemployment shows problems in the school-to-work transition; old-age unemployment shows a lack of the relevant skills or institutional barriers to employment.

Continued

Table 3.3 Mismatch indicators: definitions and interpretation (cont.)

Indicator	Definition	Purpose	Data source(s)	Interpretation
NEET	IA+U/POP	Examines non-employment among young people in the school-to-work transition (expressed as unemployment or inactivity not related to participation in education)	LFS	The share of young people who are neither working (after education) nor in education provides insights into the barriers encountered when entering the labour market, including the lack of relevant skills.
Over-education	Percentage with education level above required or identified level of education in occupation (group)	Degree of mismatch by qualification level	LFS, skills surveys	Higher percentages of over-education (or an increase) reflect higher mismatch.
Under-education	Percentage with education level below required or identified level of education in occupation group	Degree of mismatch by qualification level	LFS, skills surveys	Higher percentages of under-education (or an increase) reflect higher mismatch.
Coefficient of variation	Ratio of standard deviation to the mean, e.g. compares the distribution of skills within different groups in an attempt to determine the variation between the two distributions	Comparison of differences in education level among employed and unemployed people	LFS	Increasing levels indicate higher skills mismatch.
(Relative) wage rates	Various definitions Mostly index of wages relative to base year (and relative to specific base level)	Examines the overall level at a specific time, also the development over time	LFS, wage surveys, administrative (tax or social security) data	Increasing (relative) wages usually indicate a higher (relative) demand for the specific group, i.e. an increase in the wages of people with a higher level of education relative to those with an intermediate level of education reflects higher relative demand for those with a higher level of education.

Notes: POP – population, U – unemployed, IA – inactive people (for NEETs calculation, only non-education inactivity is taken into account). The population is, by definition, the sum of employed, unemployed and inactive people (POP=U+E+IA), while the labour force is defined as unemployed plus employed people (LF=U+E).

Additional data is often more diverse and can be obtained from various sources. Here we provide some examples of using alternative data sources that were available in at least one of the seven pilot countries.

Self-assessed mismatch indicators

Self-assessed indicators of skills mismatch can be derived by asking direct questions about the adequacy of skills. They can also be derived indirectly by asking about the required skill level in a position (e.g. occupation, job) and about the skill level that is employed in that position. Typical investigation instruments are self-assessment of skills and qualifications usage (e.g. tracer studies, PISA, PIAAC), employers' surveys and occupational or skills needs analyses.

These indicators excel in their simplicity, as they seem straightforward to interpret. If there is a difference between the skill level a person has and the skill level perceived to be necessary for a position, we could speak about a skills mismatch. This simple comparison requires several assumptions. Depending on the type of survey, the specific wording of the question and the general set-up, a mismatch might be presumed when there is simply a bias towards specific types of answers. A simple example might help understand this: when asking former management graduate students about the skill level they have and the skill level they actually need in their company, for example, there is often a discrepancy between the perceived skill (which is high) and their actual usage of the skill in their job. This is the simple result of initial job levels in a hierarchy requiring much fewer (strategic) skills, which might become more important later on in their career.

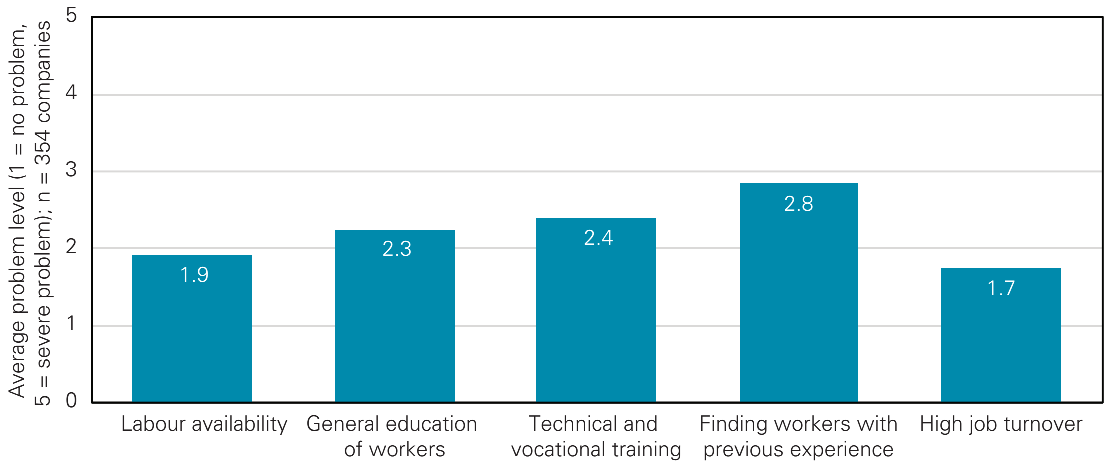
Employers tend to overemphasise a lack of skills and underestimate over-skilling. They notice when their staff fall short of the required skills but it is much harder to observe that their staff have unused skills. There can also be a tendency to compare, e.g. job applicants with the initial, idealised description of a vacancy. Both of these effects would lead towards a bias in favour of 'lack of skills'.

However, it should also be noted that attaching specific skill requirements to jobs, especially if we identify jobs by aggregate occupations, is an oversimplification. In reality, any job will require its own specific bundle of skills, which can sometimes be more or less demanding. The actual skills to be used and the way in which the work is organised are often only determined once a match has been made, i.e. a specific person has been hired (see also Handley et al., 2017, p. 49ff). Standard LFS surveys will not allow to work in such a fine grained manner as they do not provide such detailed information. More specialised surveys can attempt to bring together the distribution of people's skills and tasks involved in particular jobs to understand these processes.

Figure 3.1 provides an example from Georgia's STEP employers' survey. The STEP project attempted to bring together background information on workers with, in some countries, information on employers. In the data used, shortcomings in the labour market were investigated, specifically with respect to skills mismatches on a Likert scale. On this scale, 5 indicates severe problems and 1 indicates no problems for employers. While general availability of labour is seen as less of a problem, the more specific the skills are, the more employers – on average – estimate labour shortages as problematic. This tendency to see the situation as problematic increased with general education and rose further when (specific) technical and vocational training was required. The highest value was reached when specific work experience was required. This is not necessarily specific to the Georgian labour market, rather it should illustrate that the specificity of some skills makes it hard for employers to find an ideal candidate for vacancies. While education and even technical skills can be solved by the education system, experience has to be gained in the labour market.

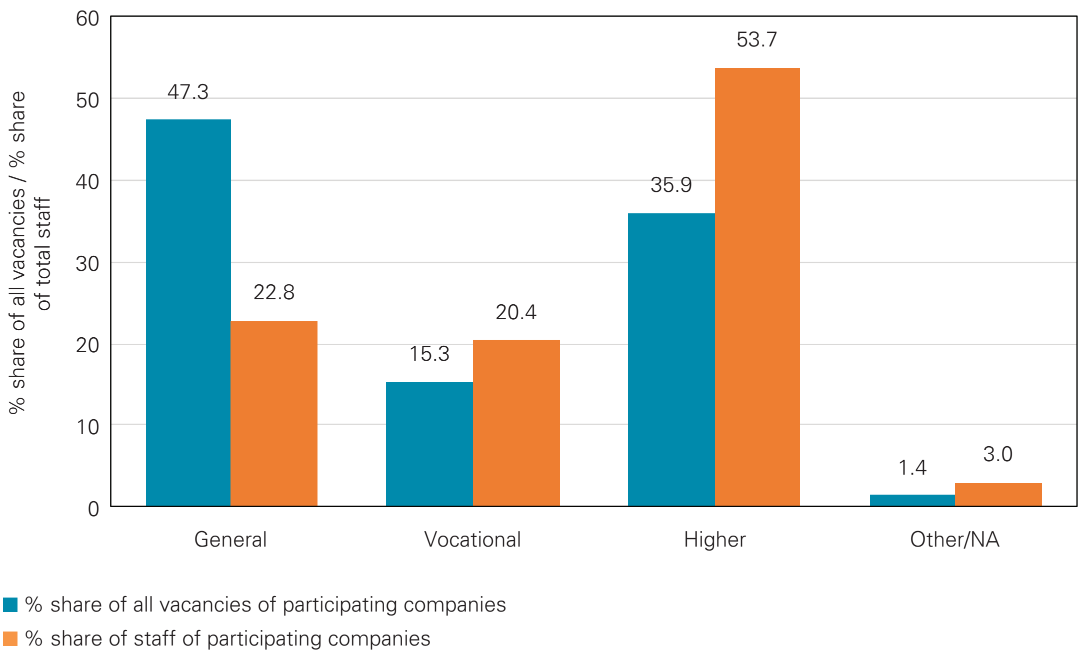
An indirect approach is shown in Figure 3.2, where the skill level of existing staff is compared to the skill requirement of vacancies. Again, the data should be interpreted carefully. While the skill level required in the vacancies shows the general direction in which the economy – as represented by the firms

Figure 3.1 Assessment of labour market shortages by employers in Georgia, 2012



Source: STEP 2012 Georgia, authors' calculations

Figure 3.2 Skill level required for vacancies versus skill level of staff in Georgia, 2015



Source: Georgian survey on labour market demand (employers' survey) 2015, authors' calculations

interviewed – is moving, the distribution of the education level within the firms can be seen as the current status quo in terms of skill use.

There could be an argument in terms of how forward looking are firms in anticipating the skills that will be required from now on and in the future. On the other hand, it might also be interpreted in terms of current disequilibrium: if the skills of the current workforce deviate from what is required, the workforce could then be considered to be inadequate in terms of skill mix. This would imply a current mismatch, whereby it is assumed that firms are unable to fulfil their requirement for a specific mix of skills.

In the case of Georgia (Figure 3.2), the vacancies show a much higher demand for general education than vocational or higher education. This could imply that the new, potentially additional, positions predominantly require a lower level of skills or a lower degree of skills' specialisation, thus indicating how the labour market is potentially changing. It could imply that there are positions filled by individuals with higher or vocational training that is not required for the specific position, thus pointing towards current over-qualification within the workforces of the firms interviewed. This would imply that the vacancies are somewhat representative of all positions within the firms.

A similar assessment could be attempted for the Serbian data on hiring difficulties (Table 3.4). Here, however, the dimension is occupation rather than qualification or skills. In addition, we are missing the counterpart of what is available (supply or current staff). As before, a lack of knowledge and skills and a lack of work experience are important factors in all cases. Work experience becomes particularly important in higher-level occupations.

Table 3.4 Companies that encountered difficulties in filling vacancies in Serbia by kind of difficulty and occupation searched, 2017

Occupation required (ISCO 08)	Difficulties encountered in the labour market							Companies that encountered difficulties when searching for this occupation (number of cases)
	Labour market	Educational system deficiencies	Inadequate level of education	Lack of knowledge and skills	Lack of work experience	Unsatisfactory working conditions	Other reasons	
01 Managers	4.8	4.8	0.0	42.9	33.3	14.3	0.0	21
02 Professionals	32.0	2.7	3.0	25.3	24.2	2.0	10.8	297
03 Technicians and associate professionals	13.7	0.8	6.1	29.0	31.3	0.8	18.3	131
04 Clerical support workers	9.4	3.1	6.3	34.4	25.0	6.3	15.6	32
05 Services and sales workers	11.1	4.0	6.1	30.3	19.2	10.1	19.2	99
06 Skilled agricultural, forestry and fishery workers								2
07 Craft and related trades workers	29.5	4.2	4.5	28.5	23.9	1.3	8.1	762
08 Plant and machine operators and assemblers	22.5	4.7	3.1	26.2	24.1	3.1	16.2	191
09 Elementary occupations	7.2	1.2	3.6	32.5	14.5	6.0	34.9	83
Average	24.9	3.5	4.2	28.2	23.9	2.7	12.5	1 618

Source: Serbian employers' survey, 2016, authors' calculations

The difficulties of young workers in the labour market can be examined using data provided by individuals. Tables 3.5 and 3.6 provide examples of labour market outcomes relative to qualification outcomes. The data provided for Georgia is based on the UNICEF youth survey of 2017. The data provided for Egypt is based on the Egypt Labour Market Panel Survey (ELMPS) and can be used more broadly by analysing the life cycle of employment.

Table 3.5 shows the different labour market outcomes for young people across the various age groups. These are divided up into two additional subgroups: school dropouts and those who studied a profession. School dropout is more common among those who cannot find gainful employment. Dropping out of education very often leads to unpaid subsistence work; studying for a profession leads of course towards normal employment. Higher levels of completed education also tend to be related to better labour market outcomes.

Table 3.6 shows employment histories, mimicking the full identification of employment spells or employment spell duration. Longer uninterrupted employment spells should be seen here as an indication of a good match, whereas interruptions indicate problems in the match. Taken together and analysed with respect to additional human capital and background variables, it may be possible to identify qualifications (or skills) that lead to stable employment histories, while others might be more prone to interruptions. These are, however, very data-intensive tasks.

Table 3.5 Employment structure for young people (15–29) in Georgia, 2017

Group	Education level	% share of 15–19 age group			% share of 20–24 age group			% share of 25–29 age group		
		Dropped out	Studied a profession	Total	Dropped out	Studied a profession	Total	Dropped out	Studied a profession	Total
Persons employed	Low	0.4	0.0	1.4	0.3	0.0	0.7	0.4	0.0	0.5
	Medium	0.3	1.0	3.9	1.9	3.8	15.8	1.4	4.5	9.0
	High	0.0	0.0	0.0	0.1	9.6	9.6	0.0	19.0	19.0
Unpaid and subsistence work	Low	2.3	0.5	12.7	0.4	0.0	1.1	1.9	0.0	2.9
	Medium	0.3	0.8	6.1	0.8	3.3	16.4	0.8	5.4	19.2
	High	0.0	0.0	0.0	0.0	2.6	2.6	0.0	4.9	4.9
Not employed, searched for work	Low	1.1	0.0	2.2	0.4	0.0	1.2	0.6	0.0	0.6
	Medium	0.9	0.7	6.5	2.2	5.3	16.8	1.4	4.3	9.9
	High	0.0	0.0	0.0	0.1	8.0	8.0	0.4	11.2	11.2
Not employed, did not search for work	Low	2.9	1.3	52.3	1.9	0.0	2.6	0.4	0.0	0.9
	Medium	0.3	0.8	14.7	2.8	4.3	21.9	1.5	5.2	13.6
	High	0.0	0.0	0.0	0.0	3.3	3.3	0.1	8.1	8.1
Total (% share of age group)	Total	8.4	5.1	100.0	10.9	40.0	100.0	8.8	62.7	100.0

Source: Georgian national youth survey, 2017 (UNICEF), authors' calculations

Table 3.6 Employment participation history by age group in Egypt, 1998, 2006, 2012 (% of age group)

Age group (in 2012)	Employed 1998, 2006, 2012	Employed in two periods (employed in 2012 and 2006, not employed in 1998)	Employed in one period (employed in 2012, not employed in 1998 and 2006)	Employment spells (not employed in 2012 and 1998, employed in 2006)	Not employed in one period (not employed in 2012, employed in 1998 and 2006)	Not employed in two periods (not employed in 2012 and 2006, employed in 1998)	Not employed in 1998, 2006, 2012
< 14	0.0	0.3	2.9	0.0	0.0	0.0	96.8
15–19	0.0	1.4	11.9	1.3	0.0	0.0	85.3
20–24	0.6	8.8	25.6	4.3	0.3	0.4	60.0
25–29	4.5	23.0	29.1	6.0	0.3	1.0	36.2
30–34	18.1	31.2	10.4	5.8	1.3	1.8	31.5
35–39	29.0	20.1	6.1	6.0	1.9	1.7	35.2
40–44	43.9	7.9	3.4	5.6	3.6	3.2	32.4
45–49	51.5	5.5	2.8	4.3	2.9	1.6	31.4
50–54	49.1	3.4	1.6	6.4	5.1	1.9	32.4
55–59	47.9	3.1	2.1	4.4	6.9	2.9	32.8
60–64	21.7	1.2	1.2	5.1	25.7	5.6	39.5
65–69	11.0	1.2	1.7	4.4	19.2	15.9	46.7
70–74	11.3	1.5	1.0	4.6	8.8	23.7	49.2
75–79	4.7	0.5	0.0	5.4	10.4	11.2	67.8
80+	1.7	1.4	0.3	5.3	11.1	5.4	74.9

Source: ELMPS panel survey in Egypt, 1998, 2006, 2012 (Economic Research Forum), authors' calculations

3.3 Data preparation

Once country data and background information were collected, the international research team proceeded to harmonise the data. This included aggregating the data by labour market status or educational attainment level. The statistical significance and reliability of the data were also assessed. The results are summarised below.

Harmonisation

Egyptian and Georgian microdata could be imported into Stata (software for statistics and data science). For the other countries, national experts were given instructions beforehand on how to aggregate variables. They inserted aggregate data tables in the data collection template in Excel. This data had to be restructured to make it readable in Stata. After these initial preparations, we created harmonised variables that allow us to calculate several basic labour market and skills mismatch indicators at a later stage.

Please note that Egyptian LFS data came from two different sources: datasets prepared by the Egyptian Economic Research Forum (ERF)[9], which were based on data collected by CAPMAS and were available up to 2014. Only unprocessed CAPMAS LFS microdata was available for 2015. This meant that we had to prepare this dataset separately. After harmonisation, the CAPMAS dataset was merged with the ERF dataset. Data for Georgia and Egypt was updated during the project phase to include more recent data and weightings.

The chosen dimensions reflect a compromise between detail and comparability. They are developed based on the commonly available dimension in most countries.

Tables 3.7 and 3.8 illustrate how a particular variable is generated for all the countries (labour market status and education, respectively). Although variables are 'pre-harmonised' by national experts in Morocco and Serbia, a variable to capture this information in a single cross-country variable with the same categories (labour market status) had to be created. Other variables that were harmonised in a similar way include educational attainment level (Table 3.8), age group categories, gender categories, period of unemployment, an indicator for persons who are currently in school, occupation, or other more specific variables for calculating skills mismatch indicators (e.g. generating a variable identifying persons with upper secondary education in elementary occupations, which is needed to calculate the occupational mismatch indicator).

Vocational education was difficult to identify in most countries. Table 3.8 reflects the identification strategy. Ideally, further identification of education level and type of education (vocational or non-vocational) would allow us to analyse the impact of different forms of education in a more consistent manner.

Table 3.7 Aggregation of labour market status

Aggregated level	Egypt	Georgia	Moldova	Montenegro	North Macedonia	Serbia
Employed people	Variable lfpst == 1 (up to 2014) / Variable mas == 1 (2015, 2016)	Variable Aqt == 1	Aggregated by the national expert or the relevant national institution			
Unemployed people	Variable lfpst == 2 (up to 2014) / Variable mas == 2 (2015, 2016)	Variable umush_mkacri == 1				
Inactive people	Variable lfpst == 0 (up to 2014) / Variable mas == 3, 4, 5, 6 (2015, 2016)	Variable araaqt == 1				
People younger than 15 years	Variable age_group == 1	Variable age_group == 1				

Note: Due to low comparability and insufficient variables, Moroccan data is not included in this analysis.

[9] See www.erfdataportal.com/index.php/catalog/125

Table 3.8 Aggregation of educational attainment levels

Aggregated level	Egypt	Georgia	Moldova	Montenegro	North Macedonia	Serbia
Low	Illiterate	Illiterate	Primary or no education	ISCED 2011 0-2	ISCED 2011 0-2	Without education
	Can read and write	Does not have primary education but can read and write	*Gymnasium*			1–3 grades of primary education
	Literacy certificate	Primary education				4–7 grades of primary education
	Primary and preparatory	Lower secondary education				Primary education (eight years)
	Primary					Lower secondary education lasting 1–2 years
	Preparatory					Lower secondary education lasting 3 years
Intermediate, non-VET	Academic secondary	Upper secondary education	Secondary school	ISCED 2011 3-4_gen	ISCED 2011 3-4	Upper secondary education lasting 4 years
	Post-secondary					Grammar school
						Specialisation after secondary education, school for highly qualified workers
Intermediate, VET	Vocational secondary	Secondary professional programme	Secondary professional	ISCED 2011 3-4_voc		
		Vocational programme	Secondary specialised			
		Higher professional programme				
High	University	Bachelor or equivalent	Higher	ISCED 2011 5-8	ISCED 2011 5-8	High level of education, first level of faculty (old programme)
	Postgraduate	Master or equivalent				Faculty, academy, undergraduate academic studies, high level of applied education, specialised academic studies
		Doctor or equivalent				Master's in academic studies, integrated studies (medicine, pharmacy, stomatology and veterinary science – Bologna)
						Doctorate in academic studies

Source: Authors

Table 3.9 describes the sources and variables for income aggregation.

Table 3.9 Aggregation of income

Aggregated level	Income
Egypt	Variable dlywg (daily wage, assuming a five-day working week for regular workers)
Georgia	Variables ShemDaq + ShemTviTdasaqm (income from self-employment and dependent employment)
Moldova	Aggregated by national expert or relevant national institution (obtained from the household budget survey)
Montenegro	Aggregated by national expert or relevant national institution
North Macedonia	Downloaded from Eurostat
Serbia	Aggregated by national expert or relevant national institution

Calculation of skills mismatch indicators[10]

The harmonisation of basic variables facilitates the calculation of harmonised indicators. In theory, at this stage a cross-country database could have been created by simply combining national datasets. However, due to data incompatibilities (in particular between Morocco and the other countries), it was more practical to calculate indicators separately for each country[11].

Given the availability and reliability of the data and the feasibility of comparing across countries, a number of indicators (that could indicate the context and incidence of skills mismatches) were created for each country, namely:

- coefficient of variation (CVAR) by educational attainment level;
- unemployment rate by educational attainment level and age group;
- proportion of unemployed vs. employed people by educational attainment level and age group;
- proportion of inactive vs. employed people by educational attainment level and age group;
- proportion of non-workers (unemployed + inactive) vs. employed people by educational attainment level and age group;
- occupational mismatch indicator;
- unemployed people by period of unemployment and educational attainment level;
- variance of relative unemployment rates;
- relative wages by educational attainment level (if robust income variable is available);
- (young) people who are not in employment, education or training (NEET) by age group – if information on current school attendance is available (in Egypt, Georgia, Montenegro, Moldova and North Macedonia);
- empirical method indicator.

Each indicator can be easily calculated for several age groups, by different education level, several combinations of subgroups of the labour market (unemployed, inactive, employed, or – in the case of Egypt and Georgia – dependent or self-employed) or by other characteristics (e.g. specific sectors could be excluded).

Results for all countries were exported into a single Excel file. Each indicator for each country was exported into a single sheet.

10 The processing of the combined data and the calculation of the indicator was programmed in Stata.

11 For example, in contrast to the other six countries, aggregate data in Morocco did not contain unemployment by five-year age group. Also, age groups were not congruent in the Moroccan data. Several changes therefore had to be made to adapt the calculation to Moroccan aggregate data.

Calculation of non-LFS-based tables and figures

Questionnaires or databases used in non-LFS-related national surveys were analysed for variables that indicate skills mismatch. Non-LFS data was therefore used for gathering country-specific additional information that might not be covered in the national LFS data. This information was processed in Stata and is shown in Excel tables or figures.

3.4 Data availability and limitations

This section describes the methodology used for gathering and checking data availability and reliability, the calculations made for key indicators (relating to context and skills mismatches) and the limitations revealed during data processing.

Data availability

To check for data availability in the seven participating countries, national experts completed a data availability questionnaire. This questionnaire had been prepared by the international experts to check which variables could be extracted from the national LFS to create skills mismatch indicators later on. Information on the availability of additional non-LFS data sources was also collected in the questionnaire. This allowed us to anticipate the countries where data might be limited. Following this, the data collection process was initiated.

A trade-off had to be made with respect to the availability of data and comparability across countries. In general, the collection strategy was to gain access to microdata that would allow for the direct calculation of indicators along all dimensions while at the same time allowing the team to adapt to different categorisations and bracketing (especially age brackets). Given the limited access to microdata, this was only possible for two countries. In all other countries, the data was collected according to the data collection template that included the required breakdown to calculate the imbalance indicators.

2016 was chosen as the base year to present the cross-country results as data was available for all countries for this year. More recent data was not accessible in all countries included in this report.

Data limitations for skills mismatch measurement

As stated above, the research team compiled the full datasets available from countries and attempted to calculate key skills mismatch indicators. At the same time, they assessed the comparability level across countries. While here we focus on methodological insights and limitations, further comparative results are discussed in more detail in Chapter 4.

Unemployment rate and unemployed/employed ratios

The unemployment rate calculates the rate of unemployed people relative to the population that is active in the labour market (the sum of employed and unemployed people). Higher rates show an increasing mismatch between supply and demand. Related to this are the Unemployed to Employed ratios, which express the magnitude of the number unemployed. A ratio of 0.1 implies that for each unemployed person there are 10 employed persons, while 1 implies a one-to-one relationship. These indicators can be calculated separately for education levels. Ratios can also be calculated for inactive persons, e.g. by calculating the employed to working-age population ratio.

These indicators require that data on unemployed, employed and inactive people are available disaggregated by education level and, ideally, by age group. The main limitation is therefore the unreliability of the data due to a small number of observations, specifically for unemployed people, as these are usually the smallest sub-population (see Table 3.10).

Raw LFS data is weighted to account for the population size of the relevant country. As a general rule of thumb, labour force surveys conducted in countries with a bigger population (Egypt, Georgia, Serbia) should enable a more detailed analysis than those conducted in countries with a smaller population (Moldova, Montenegro, North Macedonia) as the total number of observations in the LFS sample should be higher. As unemployed people are usually the smallest sub-population group, the number of observations for unemployed people contained in a national LFS can be used to assess the level of detail that can be calculated for the indicators. For example, although the population of Moldova aged 15 to 64 (2.99 million) is twice as large as that of North Macedonia (1.46 million), the number of unemployed people in Moldova is significantly lower. This means that due to the low number of observations of unemployed people, the reliability of indicators that are dependent on unemployment data (like the unemployment rate or unemployment ratio) might be lower in Moldova when compared to North Macedonia. This weighting process, however, causes variations between weighted and raw data.

As seen in Figure 3.3, unemployment rates in Georgia (2016) calculated from the raw, unweighted sample data (blue column, each observation has a weight of 1) are lower than official unemployment rates. Official unemployment rates are calculated from weighted data (yellow column), and each observation has a weight between 143.8 and 1 537.6 depending on how well an observation (that means an individual who participated in the LFS) is represented in the sample compared to the whole population.

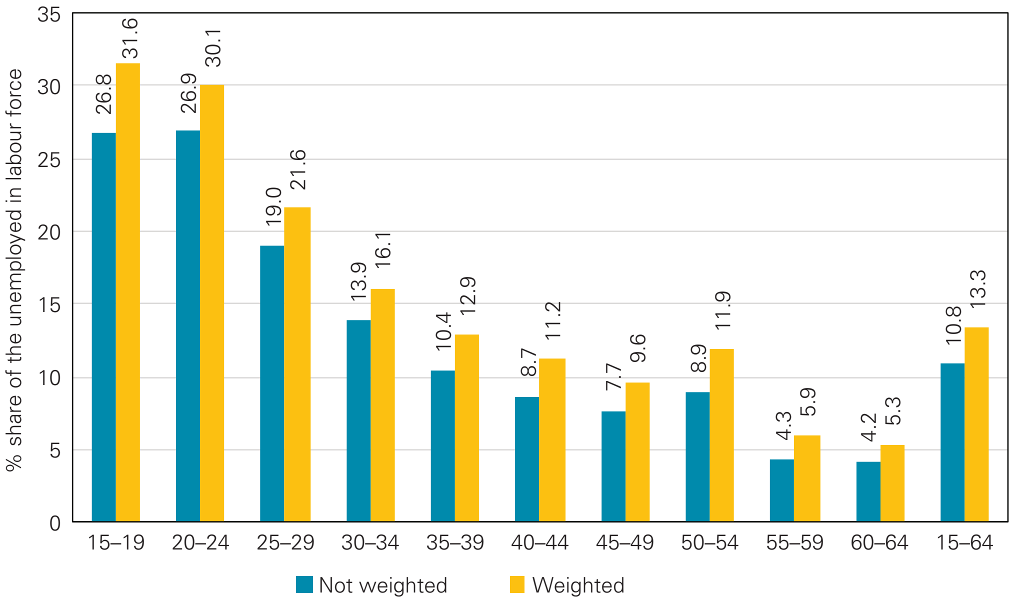
Weighted data creates a false impression of data reliability. Table 3.11 shows unemployment rates for a small, and therefore underrepresented, group

Table 3.10 Population by labour market status, 2016 (in thousands)

	Egypt	Georgia	Moldova	Montenegro	North Macedonia	Serbia
Employed people	24 927	5 891	1 220	219	714	2 579
Unemployed people	3 765	1 094	53	48	225	488
Inactive people	29 961	2 679	1 713	154	517	1 609
Population	58 654	9 678	2 985	422	1 455	4 677

Note: The population is limited to include those aged 15–64.
Source: Authors' calculations using 2016 labour force surveys

Figure 3.3 Unemployment rates – not weighted versus weighted – in Georgia, 2016



Source: Authors' calculations using LFS 2016 in the LFS: persons aged 60 to 64. Weighted data indicates that unemployment rates in this age group are very high for better-educated unemployed people. However, only two survey participants aged between 60 and 64 were unemployed with a low level of education. Weighted data, however, indicates that around 592 of all Georgians fall into this category. It could therefore be true that persons in this age group with a low level of education are seldom unemployed. It is, however, much more likely that this group is underrepresented among survey participants. This means that unemployment rates for this particular group are most likely not reliable due to a low number of observations in the survey.

For this reason, national statistics offices might refuse to provide data that they regard as unreliable.

There are 13 609 unemployed people with secondary professional education in Moldova in 2017 (Table 3.12). However, no information on age structure is available as the Moldovan statistics office does not publish data if the weighted number of

Table 3.11 Unreliable unemployment rates for persons aged 60–64 by education level in Georgia, 2016

2016	Unemployment rate (60–64)		Number of employed (60–64)		Number of unemployed (60–64)	
	Not weighted	Weighted	Not weighted	Weighted	Not weighted	Weighted
Low	2.5	2.6	77	22 211.6	2	591.8
Intermediate, non-VET	2.4	3.5	782	234 191.4	19	8 580.4
Intermediate, VET	4.7	8.1	633	208 548.9	31	18 457.1
High	6.9	9.1	448	204 554.8	33	20 464.9
All education levels	4.2	6.7	1 940	669 506.7	85	48 094.1

Source: Authors' calculations using LFS 2016

Table 3.12 Unemployed in Moldova by age group and level of education (in thousands), 2017

Age group	National level of education						
	Primary or no education	Gymnasium	Secondary school	Secondary professional	Secondary specialised	Higher	Total
15–19	0.0	0.0	0.0	0.0	0.0	–	0.0
20–24	–	0.0	0.0	0.0	0.0	0.0	7.8
25–29	–	0.0	0.0	0.0	0.0	3.6	8.9
30–34	0.0	0.0	0.0	0.0	0.0	0.0	7.4
35–39	0.0	0.0	0.0	0.0	0.0	0.0	7.0
40–44	–	0.0	0.0	0.0	0.0	0.0	5.4
45–49	–	0.0	0.0	0.0	0.0	0.0	3.7
50–54	0.0	0.0	0.0	0.0	0.0	0.0	4.0
55–59	0.0	0.0	0.0	0.0	0.0	0.0	3.7
60–64	–	0.0	0.0	0.0	0.0	0.0	0.0
65+	–	–	–	–	–	0.0	0.0
Total	0.0	10.6	9.8	13.6	6.1	11.3	51.6

Note: 0.0: values less than 3 000; '–': no values (weighted) observations is below 3 000. This means that it is not possible here to calculate indicators that rely on unemployment data disaggregated by gender, education or age group.

To prevent this situation, data should be requested for broader age groups and/or less disaggregated education levels to increase the number of observations. This was the case in Montenegro: after consulting the national statistics office, we decided to collect data for three broader age groups (15–29, 30–54, 55–64) instead of five-year age bands. This is even more important when another dimension, like gender, is added to the data request. The national institution in charge of providing LFS data should therefore be contacted as early as possible to prevent these issues from becoming apparent only after the data has been delivered. Needless to say, this situation can be prevented in general if LFS microdata can be accessed directly.

Another issue that might affect all indicators that require data broken down by education level is the limited comparability of such data. This is because national educational classifications might not always be consistent with ISCED levels (see ETF, 2012, p. 7).

Input from national experts and ETF staff, as well as ISCED mapping tables provided by UNESCO[12], proved to be essential for assigning national education levels to their corresponding ISCED levels. It should be expected that national education levels might encompass several ISCED levels. It might not be possible to differentiate between VET and non-VET education levels if both are included in a single national education level category. Most often, data by programme orientation (i.e. general vs. vocational) at secondary level is not readily available. Also, some countries are more advanced than others in implementing ISCED 2011 in their national LFS. This can hamper comparisons between the countries on the incidence of mismatch for people who have VET as their highest level of educational attainment.

Compared to aggregate data, microdata allows much more flexibility in adapting education levels. Table 3.13 shows how the Georgian national educational classification has been aggregated into the four

Table 3.13 Educational mapping in Georgia

Aggregated level	National classification	Corresponding ISCED 2011 level
Low	Illiterate	0
	Does not have primary education but can read and write	0
	Primary education	1
	Lower secondary education	2
Intermediate, non-VET	*Upper secondary education (only persons who do not have/did not give information on a specific profession)*	3
Intermediate, VET	*Upper secondary education (only persons who have/gave information on a specific profession)*	3
	Secondary professional programme	3
	Vocational programme	3
	Higher professional programme	4
High	Bachelor or equivalent	6
	Master or equivalent	7
	Doctor or equivalent	8

[12] See http://uis.unesco.org/en/isced-mappings

Table 3.14 Educational mapping in North Macedonia

Aggregated level	ISCED 2011
Low	0–2
Intermediate	3–4
High	5–8

education levels used in this report. According to the UNESCO mapping tables, the national classification level 'upper secondary education' includes VET and non-VET education levels. By using a variable that identifies individuals who studied for a specific profession, we were able to identify that (some of) the individuals with upper secondary education level could be classified as having an 'intermediate – VET' level of education. Although the educational classification was not consistent with ISCED levels, we were able to differentiate between VET and non-VET education levels and to assign national classification levels to the corresponding ISCED 2011 levels.

In contrast to this, the education level classification used in aggregate data collected for North Macedonia already corresponded to three broad ISCED 2011 levels (0–2, 3–4, 5–8, see Table 3.14). However, it was not possible to differentiate these education levels any further. In this case, the educational classification was consistent with ISCED levels but it was not possible to differentiate between VET and non-VET education levels.

Young people not in employment, education or training (NEET)

This methodology calculates the rate of young people who are not in employment, education or training. The underlying reason is presumed to be some form of mismatch, as those who are not in education are generally presumed to have finished their education and should have found employment in some form. It thus combines non-participation and unemployment.

To calculate this indicator, it is necessary to request data for inactive and unemployed young people who are not participating in education by age group. If national authorities already have data on NEETs, and LFS microdata is not available, it is important to check how national definitions differ from each other. There might be inconsistencies in defining age groups (see ETF, 2012, p. 7) that might be due to data limitations (e.g. a low number of observations). For example, NEET data collected disaggregated by education level included the age groups 15–24 or 15–29 in Moldova; 15–29 in Montenegro; and 15–19, 20–24 and 25–29 in North Macedonia.

It is noteworthy that it seems to be difficult to fully compare the NEET indicator across countries. LFS design and the wording of the questions differ significantly between national surveys. This applies in particular when capturing participation (or non-participation) in education or training (e.g. a standard or reference formulation would state 'they have not received any education or training in the four weeks preceding the survey').

Variance of relative unemployment rates (by education level)

This indicator shows how unemployment deviates within education levels from the average of the entire country. The higher the value of the variance, the higher the level of mismatch. This methodology would also be applicable to subgroups such as age, gender, and (previous) occupation.

This indicator is very sensitive to outliers and is greatly affected by data quality. As seen in Table 3.15, unemployment rates for low education levels are very unstable in Georgia, and there also appears to be a break in the data from 2013 to 2014 for all education levels.

This results in a high variance of relative unemployment rates in 2011 and 2012 (Figure 3.4). This is mainly because unemployment rates for those with a low level of education are significantly lower (2011: 13.4%; 2012: 12.6%) when compared to the average unemployment rate (2011: 19.3%; 2012: 19.2%). The variance of relative unemployment rates decreases in 2013 as the unemployment rate for those with a low level of education climbs to 19.0% and therefore approaches the average unemployment rate of 18.8%. From 2014 to 2016, unemployment rates for those with a low level of education decrease to 15.3%. As the average unemployment rate decreases similarly during this period, the variance of relative unemployment rates stays at a low level.

Table 3.15 Unemployment rates in Georgia by education level, 2011–16

Education level	2011	2012	2013	2014	2015	2016
Low	13.4	12.6	19.0	15.1	12.8	15.3
Intermediate, non-VET	18.5	18.9	18.2	16.5	16.3	16.3
Intermediate, VET	15.9	16.7	15.7	13.2	13.6	12.5
High	23.5	22.4	21.7	18.9	17.1	17.2
Average	19.3	19.2	18.8	16.5	15.8	15.7

Source: Authors' calculations using LFS 2011–16

To prevent misinterpretations, it is therefore also important to check beforehand how reliable unemployment rates calculated for the selected dimension (here: education level) are. It is also important to keep the country context in mind: in the case of Georgia, a particular trend might be caused by external effects (economic or political).

As the indicator describes the relationship between unemployment rates by education level, it is very dependent on how education levels are defined. Altering the education level classification changes the unemployment rates, and therefore the variance of relative unemployment rates. Figure 3.5 shows how the values of the variance of relative unemployment rates change when a different education level classification is applied.

Coefficient of variation by skills

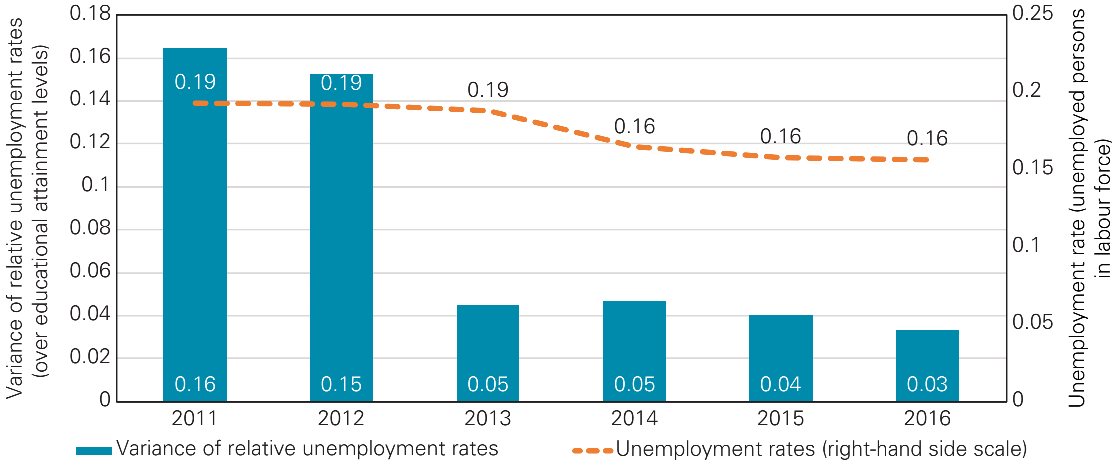
The coefficient of variation (CVAR) indicator compares the distribution of skills within different groups while correcting for the overall size of the underlying statistic. It requires data on sub-populations (e.g. employed, unemployed, inactive, working-age population) disaggregated by education levels. To make a cross-country comparison, it is advisable to select two sub-populations that provide an adequate level of data quality. As the quality of the unemployment data might not allow this level of detail (see above), it is worth considering calculating the coefficient of variation as the difference in skill composition of the employed to the working-age population instead of the employed to the unemployed population (as suggested in ETF, 2012, pp. 6–7). The CVAR is expressed in just one number, which measures the overall extent of mismatch. That means that the higher the number, the greater the difference between the skills possessed by people employed in the labour market and the skills possessed by people in the population.

It is also possible to measure the CVAR indicator broken down by age group (ETF, 2012, p. 6) or gender. As this, again, leads to a smaller sample size due to the greater level of detail, not all national LFS datasets might produce stable results. If the indicator is calculated for a very small sub-population, this might also affect surveys with a very high number of observations. For example, the CVAR for Egyptian women aged 50 to 64 is very unstable (see Figure 3.6).

The total number of observations (not weighted) in this age group ranges from 20 404 (2011) to 22 768 (2015) (see Figure 3.7) and is therefore quite high. However, as the indicator requires the total number of observations to be broken down by status in the labour market (persons employed vs. working-age population) and education level, the number of observations in the smallest sub-population within this group (women with intermediate non-VET education) is very low when compared to the total number of observations in this group. It is also noticeable that the number of persons employed is subject to fluctuations, in particular from 2012 to 2013. Therefore, the indicator should be interpreted with caution.

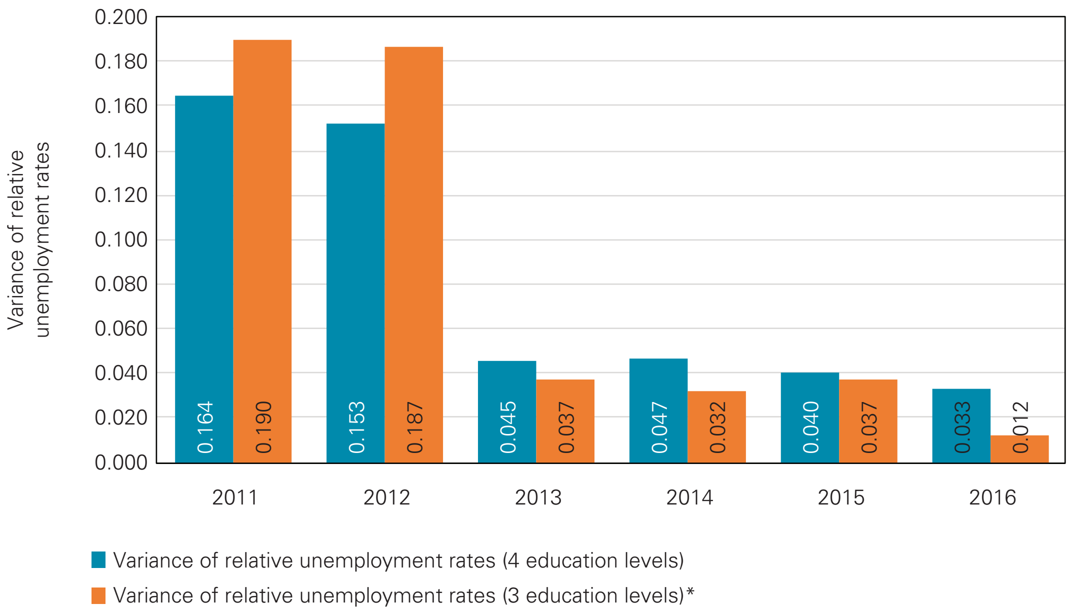
Like the variance of relative unemployment rates indicator, the CVAR indicator describes a relationship (here: between employed persons and the working-age population) that is dependent on the classification of education levels. The coefficient of variation is therefore also sensitive to the education level classification applied (see Figure 3.8). It appears that the variation between the educational attainment levels of employed persons when compared to the total working-age population is lower when using the

Figure 3.4 Variance of relative unemployment rates (15–64 age group) in Georgia, 2011–16



Source: Authors' calculations using LFS 2012–16

Figure 3.5 Variance of relative unemployment rates (15–64 age group) in Georgia – Alternative education level classification, 2011–16



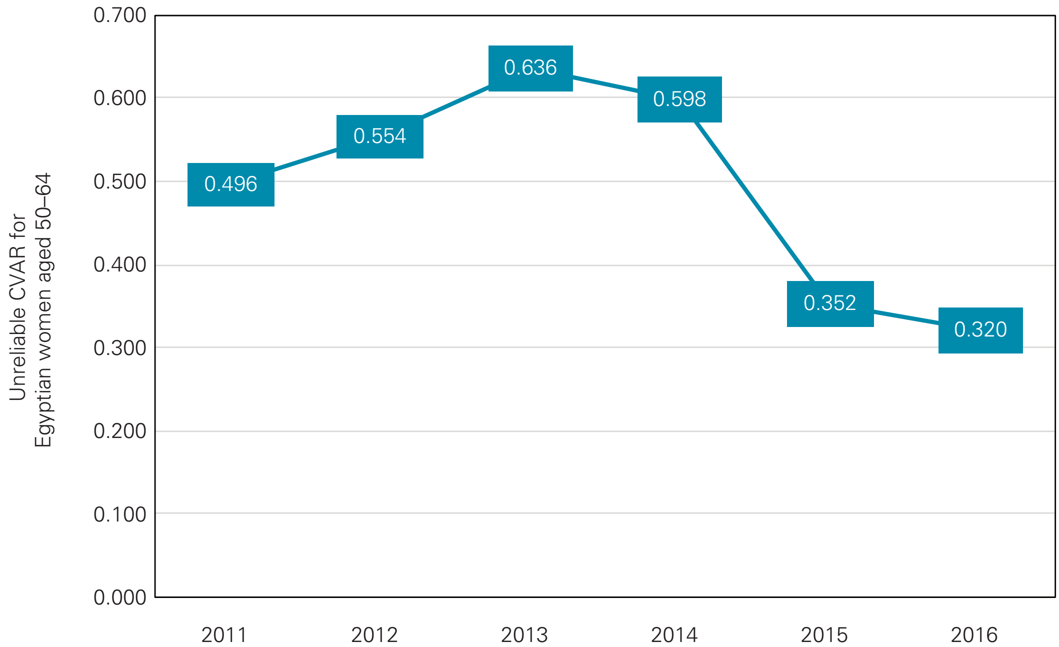
Note: (*) Three education levels (low, intermediate, high) instead of four (low, intermediate – non-VET, intermediate – VET, high)
Source: Authors' calculations using LFS 2012–16

alternative education level classification (three levels) when compared to the standard definition that makes a distinction in the intermediate education level.

Relative wages

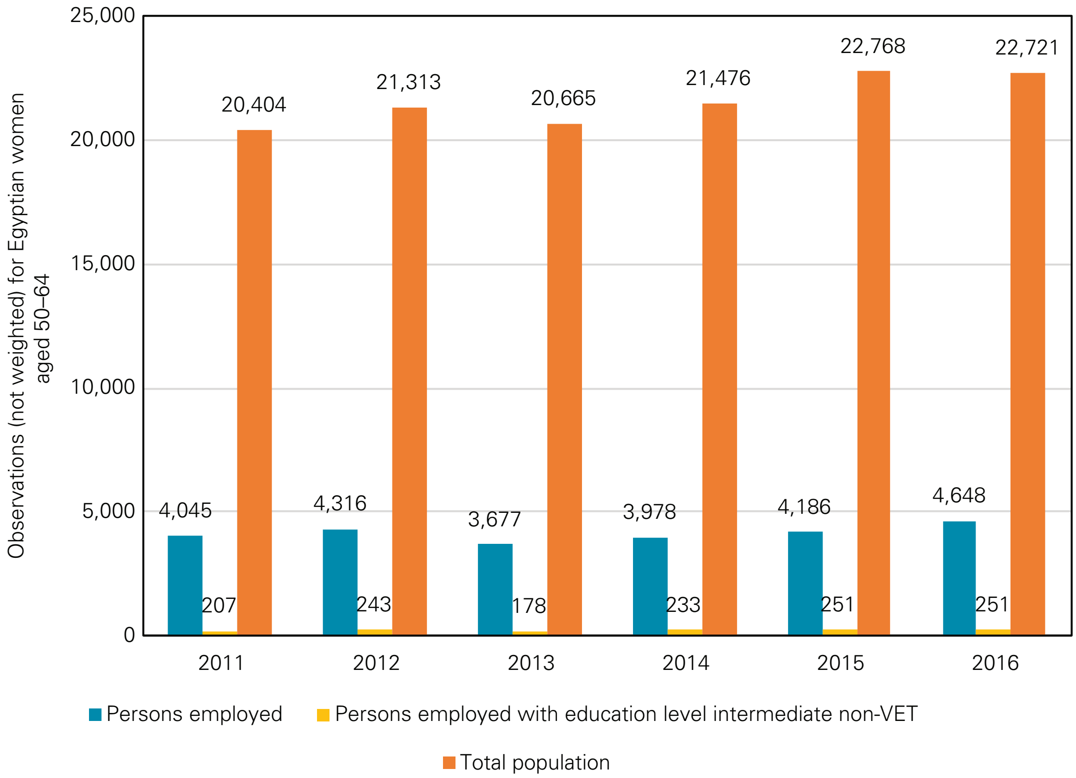
This methodology compares wages across education levels over time, either relative to a benchmark wage or indexed vis-à-vis a base year. It can usefully be plotted in a diagram, as it is then very easy to see how certain education levels are more or less well remunerated than others over time. An education level that is seen to attract a higher income than that achieved by people with other levels of education can thus be a sign that this level of education is in higher demand in the labour market.

Figure 3.6 Unreliable coefficient of variation for women aged 50–64 in Egypt, 2011–16



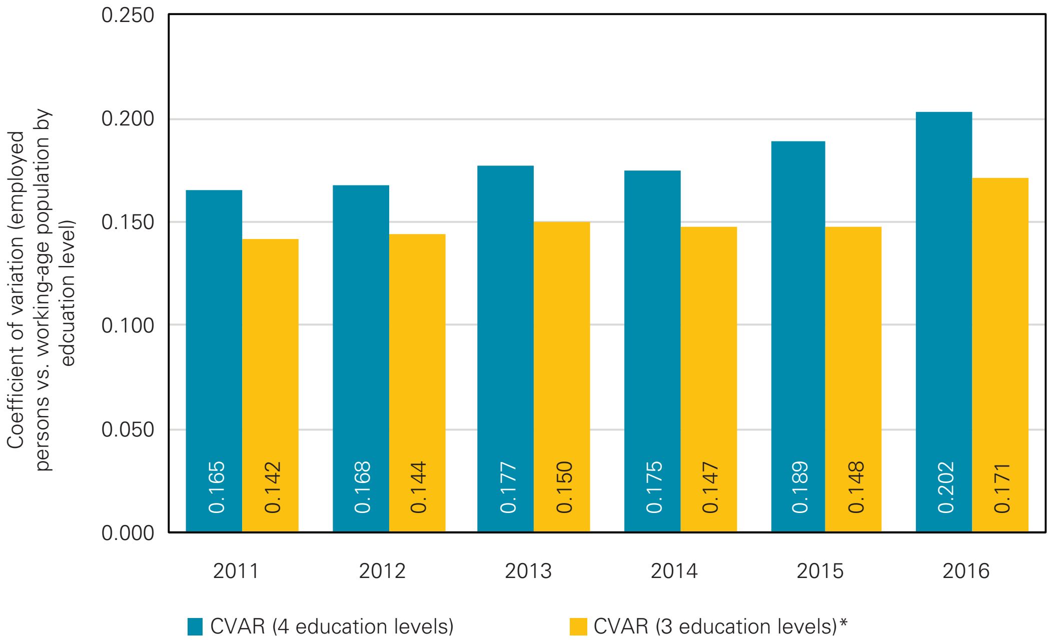
Source: Authors' calculations using LFS 2011–16

Figure 3.7 Low number of observations for women aged 50–64 in Egypt, 2011–16



Source: Authors' calculations using LFS 2011–16

Figure 3.8 Coefficient of variation – Alternative education level classification in Egypt (15–64 age group), 2011–16



Note: (*) Three education levels (low, intermediate, high) instead of four (low, intermediate – non-VET, intermediate – VET, high)
Source: Authors' calculations using LFS 2011–16

ETF staff and the national and international experts agreed to use national labour force surveys as the main source for calculating skills mismatch indicators. The main benefit of LFS data is that it is typically collected regularly and consistently. This data can provide fundamental, very detailed information on labour-market-related variables (e.g. unemployment or employment by educational attainment level and age group), which in turn can be used to calculate skills mismatch indicators. However, questions that record wage information might not be included. In this case, alternative data sources need to be consulted, e.g. the household budget survey in Moldova.

If microdata is not available or income variables are not included in LFS microdata, it is also possible that wage data cannot be aggregated as required. This is because this data is sometimes only available at household level rather than at individual level. The latter would be needed to tie it to individual education levels[13]. It might also be available disaggregated by sector or by occupation, but not by education level. And even if wage data by education level is publically available, some countries might publish data for employees only while others include all employed persons (including the self-employed). Furthermore, if data illustrates average wages or wage brackets it might not be possible to aggregate income data into categories that are comparable across countries.

Occupational mismatch

This method is based on comparisons of the ratio of people with a given education level (ISCED) working at an inappropriate skill level (measured by the International Standard Classification of Occupations, ISCO) to all workers within that ISCED level.

In this report, this indicator shows the share of persons with upper secondary education working in elementary occupations (ISCO group 9) on all persons with upper secondary education (ISCED

[13] In Moldova, income data was available at household level. It was possible to extract data relating to the income of the head of the household and link this to the education level of the head of the household. However, this still leaves out information on the income of other household members.

2011 group 3) and the share of persons with tertiary education working in semi-skilled occupations (ISCO groups 4–9) on all persons with tertiary education (ISCED 2011 groups 5–8 or ISCED 1997 groups 5–6). We follow the OECD definition (OECD, 2010, p. 346) with the exception that we calculate the indicator for the 15–64 age group instead of the 25–29 age group to avoid low cell sizes for smaller countries.

The comparability of national education levels to ISCED classifications is discussed above. The labour force surveys for all the countries use international classifications for occupational classifications. But while Georgia and Egypt use ISCO 88, Moldova, Montenegro, North Macedonia and Serbia use ISCO 08[14]. That means that the comparability of the occupational mismatch indicator between the former and the latter countries is limited.

Another problem with this indicator is, again, the sample size in smaller countries, as data needs to be reliable even if it is broken down by education level for each single occupational group.

Empirical method: Over- and under-education

This method can be used in cases where datasets do not include specific questions on over-education or over-skilling; it is nevertheless quite a simplistic measurement and must be interpreted as a proxy. The empirical method is a purely statistical measure where the distribution of education is calculated for each occupation; over-education is defined as existing when the level of education is more than one standard deviation above the mean (Bauer, 2002) or above the mode (Mendes de Oliveira et al., 2000) for the education level for a given occupation. The educational mean and/or mode for each occupation is thus assumed to be a match for that occupation, but this may very well be a false assumption. 'In theory everybody employed in a given occupation could be mismatched' (ETF, 2012, p. 12). The distribution of education is calculated for each occupation; over-education is defined as existing when the level of education is more than one standard deviation above the mean, while under-education exists when the level is one standard deviation below the mean.

As in the case of the occupational mismatch indicator, cross-country comparability is dependent on the ISCO classification used.

It should also be noted that this indicator requires access to microdata. Although it is possible to calculate the indicator for higher aggregated data, it should be calculated at individual level, as standard deviation as the main measure of over- or under-education is very sensitive to the number of observations.

Beveridge curve

'The Beveridge curve is the depiction of the relationship between the unemployment rate and the vacancy rate for several distinct points in time' (ETF, 2012, p. 8). In general, LFS data proved to be sufficient to calculate most of the indicators used in this report. The exception was the Beveridge curve as, typically for labour force surveys, no data on vacancies is collected. However, short-term employment can be used as a proxy for information on the number of vacancies, as a person who is employed for a short period of time indicates a recently filled vacancy. This proxy can be calculated if a national LFS includes information on the duration of employment. A person who is in short-term employment could be defined as a person who is employed for up to one month. In countries with a small LFS sample or in countries with a less dynamic labour market it might be necessary to adapt the definition of short-term employment to increase the number of observations (e.g. to a job tenure of up to 12 months). This also facilitates the calculation of proxy vacancy rates and therefore Beveridge curve by education level, as data on employed persons by education level is included in the LFS. This level of detail might otherwise only be possible if vacancy data was available by education level, which is less common.

Indicators calculated from non-LFS data

Non-LFS data was used to gather country-specific additional information that might not be covered in the national LFS data. Questionnaires or databases

[14] Morocco uses a specific national occupational classification, therefore comparability cannot be ensured.

containing these non-LFS-related national surveys were analysed for variables that indicate skills mismatch. However, the main drawback of non-LFS datasets is that:

1. they are not carried out structurally, or
2. even the latest rounds are fairly outdated, or
3. they only focus on one side of skills mismatch.

For example, the Georgian youth studies (FES, 2016; MLHSA, 2016 or UNICEF, 2014) facilitated a detailed analysis of topics related to skills mismatch (e.g. school-to-work transition). However, they only focus on one subgroup affected by skills mismatch (younger people) and are usually not carried out structurally (i.e. they are carried out only once or at random intervals). In contrast to this, Egyptian ELMPS survey data (published by the Egyptian Economic Research Forum) contains individual and household variables that are just as detailed as Egyptian LFS data and furthermore facilitate longitudinal analysis. However, the latest round available dates from 2012, which means that this data is not very relevant when assessing current skills mismatch.

Lastly, the Serbian employers' survey was carried out structurally and recently (2014, 2015 and 2016), but focuses only on the demand side of skills mismatch (skills needs of employers). The remaining surveys listed above (Table 3.2) have at least one of these shortcomings. The decision to focus on LFS data proved to be a practicable approach to achieve the creation of a cross-country database on skills mismatch indicators.

4. CROSS-COUNTRY COMPARATIVE ANALYSIS

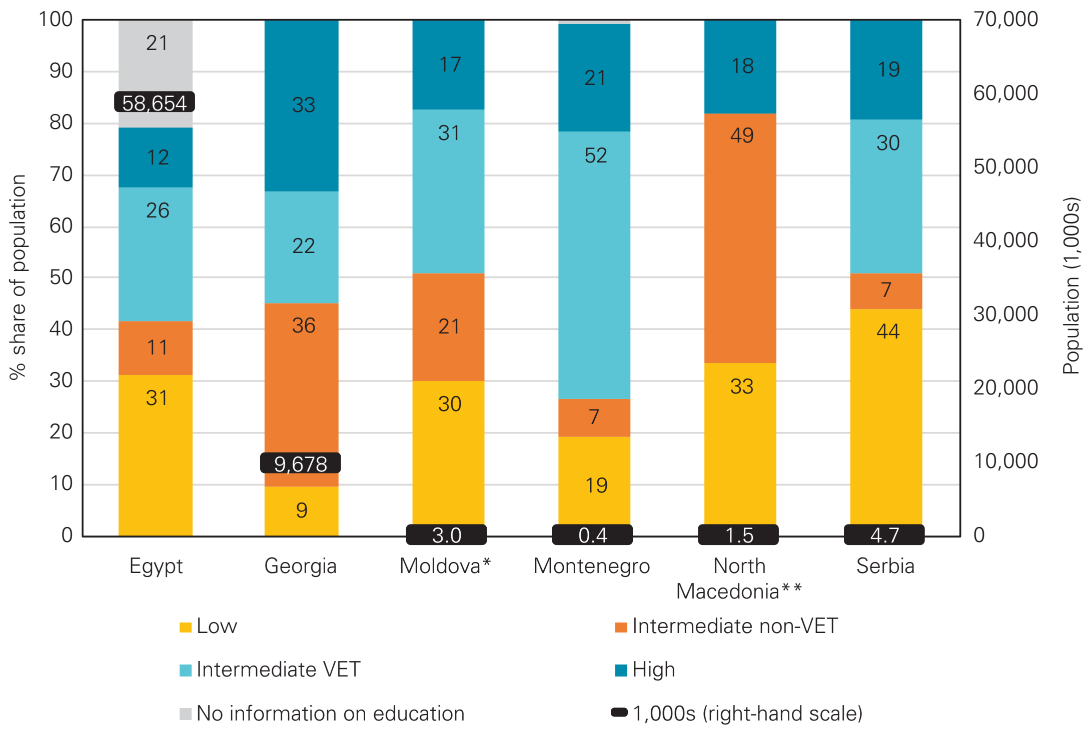
4.1 Overview

The seven pilot countries have very diverse economic and social backgrounds, as evidenced by trends in employment, education, demographic change and economic structure. Egypt and Morocco have a sizeable proportion of young people as a share of their total population (youth bulge), which puts significant pressure on the labour market (as the number of young entrants to the labour market exceeds demand). The other five countries are confronted with rather negative demographic prospects due to ageing and outmigration, which means that a shrinking workforce will become a serious risk in the future. Theoretically, fewer labour market entrants reduce the risk of a supply-demand imbalance in its most common form, i.e. high incidence or long spells of unemployment or inactivity. But transition countries like Georgia, Serbia, Moldova, Montenegro or North Macedonia are still in the process of economic restructuring, with high levels of informality, rather unattractive working conditions (e.g. wage levels) in certain sectors and insufficient job creation to match supply. Gender gaps in employment are also prominent in most selected countries, in particular Egypt and Morocco.

Education distribution is key to assessing the incidence of skills mismatches. The indicators relate to education distribution, activity rates and economic activity. A general understanding of the distribution of education levels by population (Figure 4.1), by employment (Figure 4.2), by unemployment (Figure 4.3) and by inactivity (Figure 4.4) can therefore be quite useful.

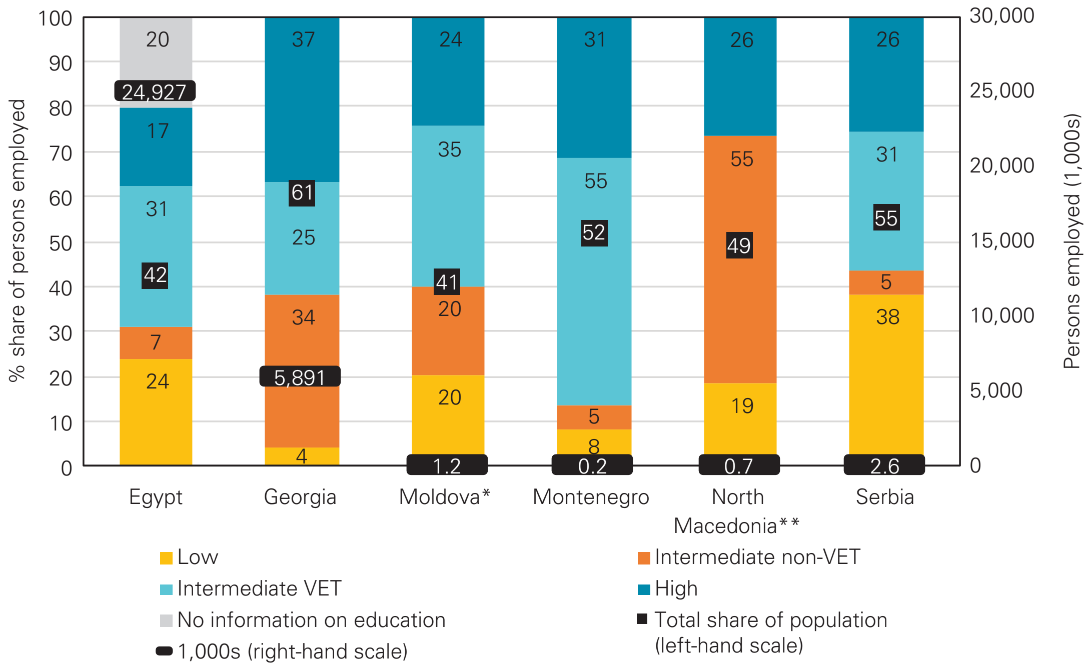
Figure 4.1 shows the differential educational attainment of the countries involved in the ETF initiative on skills mismatch measurement. Egypt is the only country in which the educational attainment of a sizeable share of the population (21%) is unknown. In Egypt, people with a higher level of education seem to account for a rather small share of the population. Intermediate education is relatively more common: about a quarter of the population has intermediate VET education, an additional 11% have intermediate but non-VET education.

Figure 4.1 Population (15–64) by educational attainment level, 2016



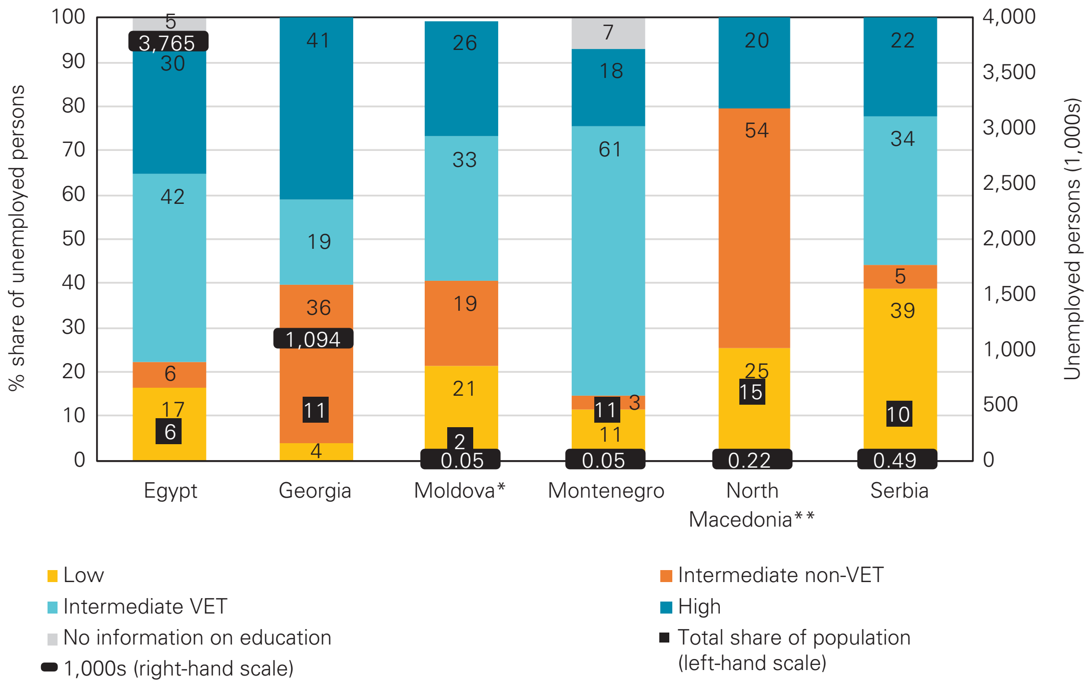
Notes: (*) Moldova: 15+ age group; (**) North Macedonia: Data does not allow us to identify VET education levels.
Source: Authors' calculations based on national LFS

Figure 4.2 Persons employed (15–64) by educational attainment level, 2016



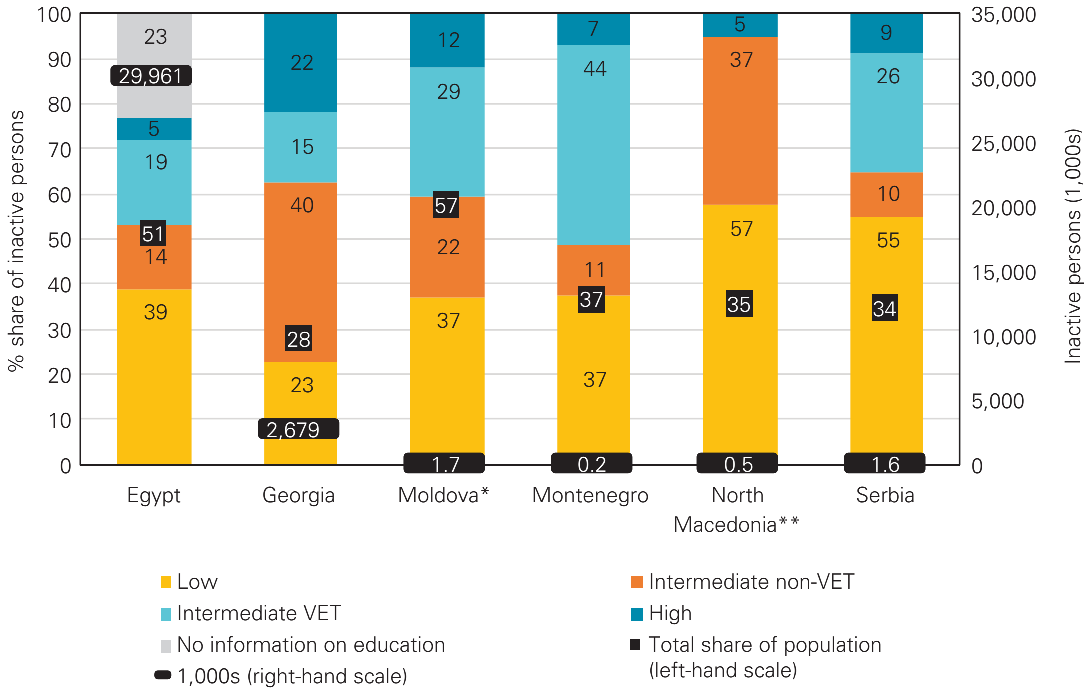
Notes: (*) Moldova: 15+ age group; (**) North Macedonia: Data does not allow us to identify VET education levels.
Source: Authors' calculations based on national LFS

Figure 4.3 Unemployed persons (15–64) by educational attainment level, 2016



Notes: (*) Moldova: 15+ age group; (**) North Macedonia: Data does not allow us to identify VET education levels.
Source: Authors' calculations based on national LFS

Figure 4.4 Inactivity (15–64) by educational attainment level, 2016



Notes: (*) Moldova: 15+ age group; (**) North Macedonia: Data does not allow us to identify VET education levels.
Source: Authors' calculations based on national LFS

A large share of the population (about one-third) has a low level of education. Similar low levels of education in the population can be found in Serbia, and to a lesser degree in North Macedonia and Moldova. In North Macedonia, available data does not allow a distinction to be made between VET and non-VET intermediate education. Georgia is notable in having a sizeable share of the population with higher education: one-third of the population compared to about one-fifth or less in the other countries.

Figures 4.2 to 4.5 are best interpreted using the shares of education within the population as a reference. This indicates that, in general, people with a high or intermediate level of education are more likely to be employed and relatively more likely to be unemployed than to be inactive. Similarly, people with intermediate VET education are more likely to be employed, while those with a low level of education are generally less likely to be in employment. Generally, people with a low level of education can be found more often in inactivity than their population share would suggest. Often this has institutional reasons. For one thing, people with a low level of education tend to be older, but also there is often not much of an incentive for them to be officially unemployed.

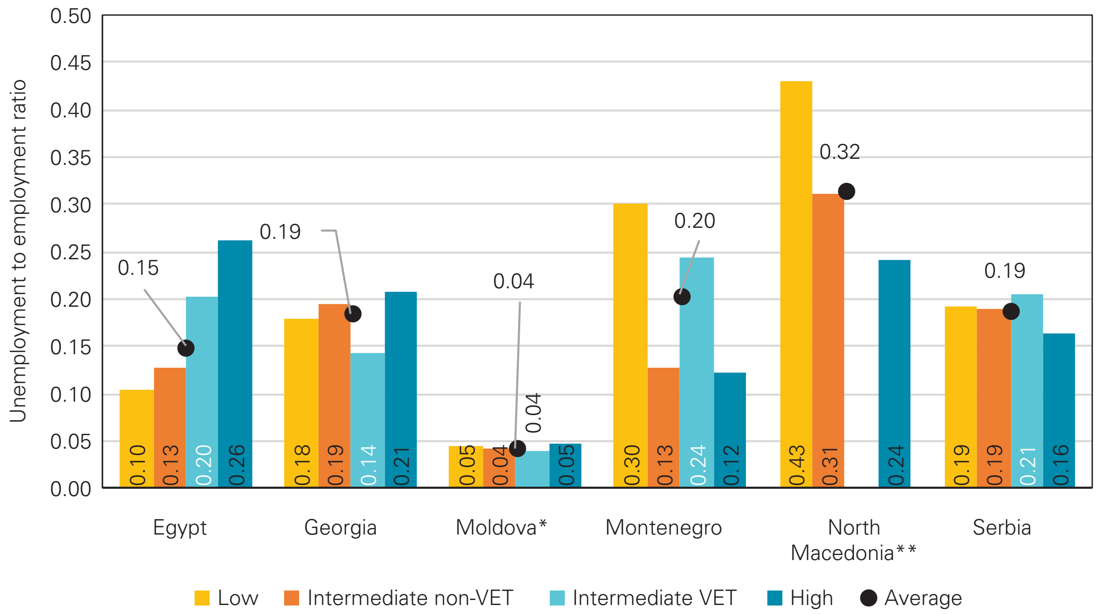
4.2 Indicators of skills mismatch

4.2.1 Unemployment rate and unemployed/employed ratios

The unemployment rate calculates the rate of unemployed people relative to the population that is active in the labour market (the sum of employed and unemployed people). Higher rates show an increasing mismatch between supply and demand.

Related to this are the unemployed to employed ratios, which provide a placid way to express the magnitude of the number unemployed. A ratio of 0.1 implies that for each unemployed person there are 10 employed people, while a ratio of 1 implies a one-to-one relationship.

Figure 4.5 Unemployment to employment ratio by educational attainment level (15–64 age group), 2016



Note: (*) Moldova: 15+ age group; (**) North Macedonia: Data does not allow us to identify VET education levels.
Source: Authors' calculations based on national LFS

Simple unemployment to employment ratios can also be used as an indicator of potential skills mismatch, especially when analysing how the supply of skills, in terms of qualifications, might fall short of what is required in the labour market. Analysing unemployment by education level usually provides an indication how heterogeneous the unemployment outcome is by these broad levels. Figure 4.6 provides a breakdown for the pilot countries. We differentiate between a low level of education, a medium level of education, a medium level of VET and a high level of education. In the unemployment-to-employment (U/E) ratio, a lower number indicates fewer unemployed people relative to the employment level. However, hasty conclusions should not be drawn from Figure 4.6. The total outcome of 0.04 in Moldova does not necessarily imply that the labour market situation there is better than that in Egypt (0.15), Georgia (0.19), Montenegro (0.20), North Macedonia (0.32) or Serbia (0.19).

In most Western economies, the ordering of unemployment rates by skill level is clearly such that unemployment rates decrease with increasing education levels. This is by no means the case in all countries. While North Macedonia follows this pattern, the rates in Moldova, Georgia and Serbia seem to be fairly similar across education levels. Montenegro spikes in low and intermediate VET.

People with VET education fare somewhat better than their non-VET-educated counterparts in Georgia and Moldova, but fare worse in Egypt, Montenegro and Serbia. However, in some countries either one group (VET or non-VET) can be rather small and heterogeneous. These outcomes by education are likely to have a multitude of underlying reasons and processes. To some extent, we might cautiously conclude that intermediate and higher education does not always provide the skills that are required in the labour market. That would indicate a mismatch by types of skills taught. Or they are providing too many graduates with skills for which there is a lack of demand. Job attractiveness or cultural factors might be also considered.

It is probably more important to think about the definition of unemployment, which requires that the person is available in the labour market, i.e. actively searching and willing to work. This excludes those people who gave up searching – potentially because of a lack of opportunities – and those people who found irregular work (if this is not covered or willingly uncovered in the LFS questions). Finally, the indicator excludes inactive people, as it examines a direct relationship between employed and unemployed people.

Gender dimension

Figures 4.6 and 4.7 provide the same ratio for men and women separately. In total, the U/E ratio is similar for Serbia (0.19 for men vs. 0.21 for women) and North Macedonia (0.33 for men and 0.30 for women). There are larger differences in Moldova (0.03 for women and 0.06 for men), Montenegro (0.15 for women and 0.20 for men), Georgia (0.22 for men and 0.14 for women), and more substantially in Egypt (0.12 for men and 0.39 for women). Thus, while in Serbia the U/E ratio is similar for men and women, in Egypt women tend to have much higher U/E ratios than men. The opposite is true for Georgia, North Macedonia, Moldova and Montenegro. Such findings may indicate a need to address the gender divide in the labour market or skills development, such as difficulties in accessing employment and/or relevant education.

Age dimension

Another way to analyse the U/E ratio by subgroup is to compare the ratio of the young (here 15–29 years) with those of prime age (here 30–54 years), as shown in Figures 4.8 and 4.9. This compares the prime-age working population to the age groups that are new in the labour market and are often still in the process of finding their way in the world of work.

As can be expected, the U/E is lower for the prime-age group in all countries. While the ratio is about three times higher for the young than for the prime-age group in Serbia and North Macedonia, it is about twice as high in Georgia, Moldova and Montenegro, and more than seven times higher in Egypt[15]. This gives an indication of how much more the young are affected by unemployment than the prime-age population. If these indicators are considered to be stable, they would hint at a problem in the school-to-work transition. This would suggest that the situation will normalise towards the level of prime-age labour market participants.

For the two countries in which microdata was available, the indicators were also calculated separately for men and women. In Georgia, men and women had similar indicators at a young age, while in Egypt the total indicator for men was 0.26 while the indicator for women was 0.97. The figures for Egypt show how the difficulty in finding employment is already amplified by the situation at a young age, most likely resulting in a withdrawal from the labour market by at least some of the women.

Unemployment duration dimension

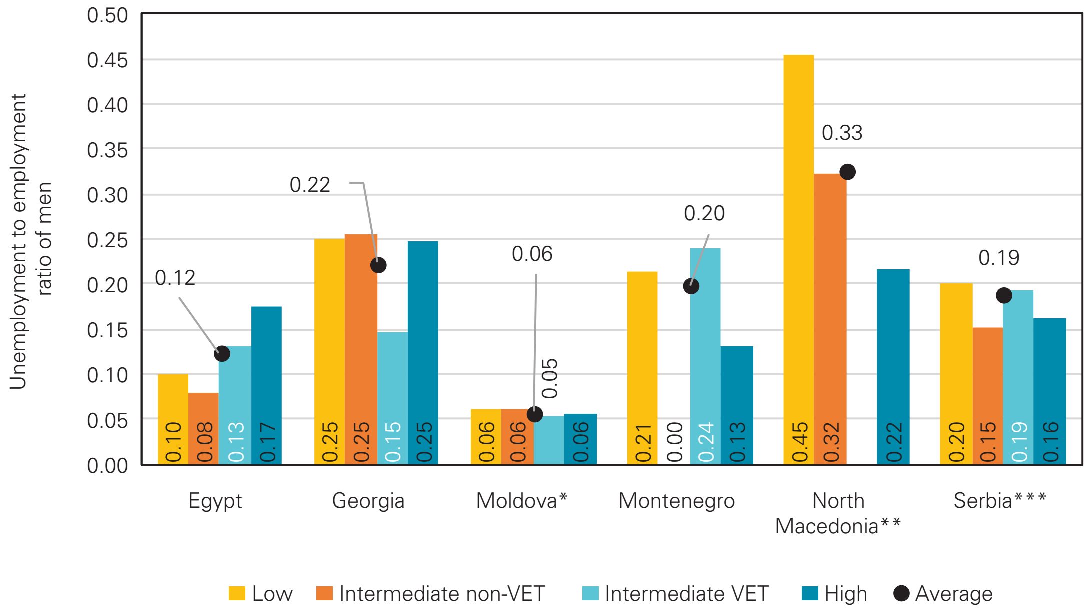
Another dimension to analyse among unemployed people is the duration of unemployment. Short-term unemployment is often seen as frictional and to some extent necessary to allow the economy and individuals to move towards new opportunities. Long-term unemployment hints more towards structural problems in the economy, but also towards the individual. The longer unemployment lasts, the more skills and knowledge become obsolete, and the harder it is for an individual to find suitable employment.

Figure 4.10 shows that North Macedonia, Montenegro, Egypt, Serbia and, to a lesser extent, Georgia have a high share of long-term unemployment, whereas the share is minor in Moldova. In terms of policy, it is always a goal to diminish long-term unemployment as much as possible, or to avoid future generations ending up in long-term unemployment.

The life cycle view on employment, unemployment and inactivity is also important background information to review even if the skills mismatch is the main point of interest. Figures 4.11 to 4.13 provide a good overview of the employment trend in 2016 over the life cycle (in orange), the unemployment (in dark blue), and the share of inactive people (in light blue). The usual pattern appears in all countries.

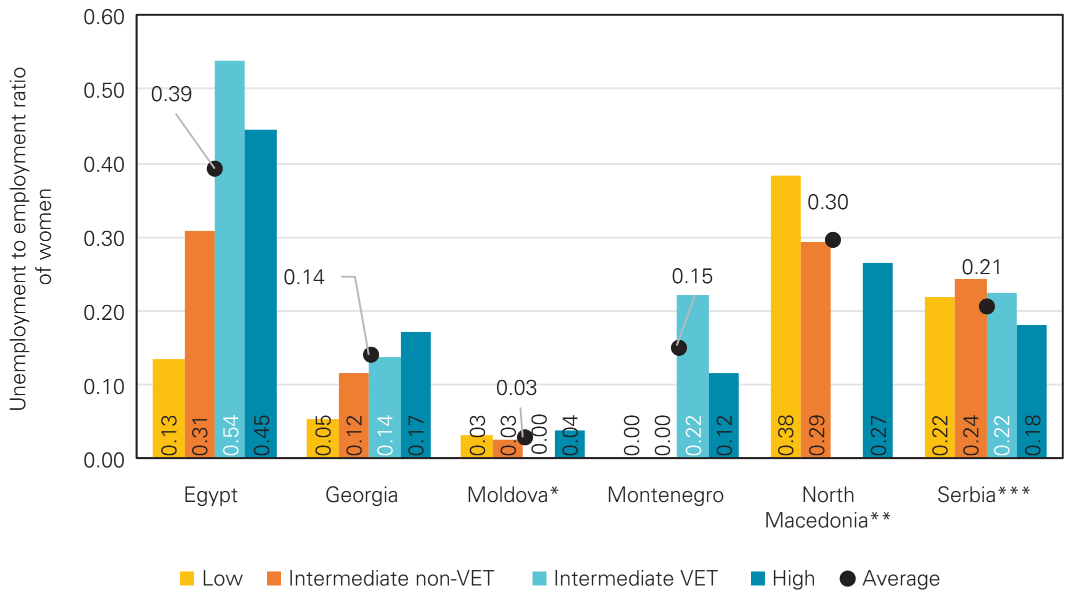
15 Unfortunately, the available data did not allow for a breakdown by age for Morocco.

Figure 4.6 Men – Unemployment to employment ratio by educational attainment level (15–64 age group), 2016



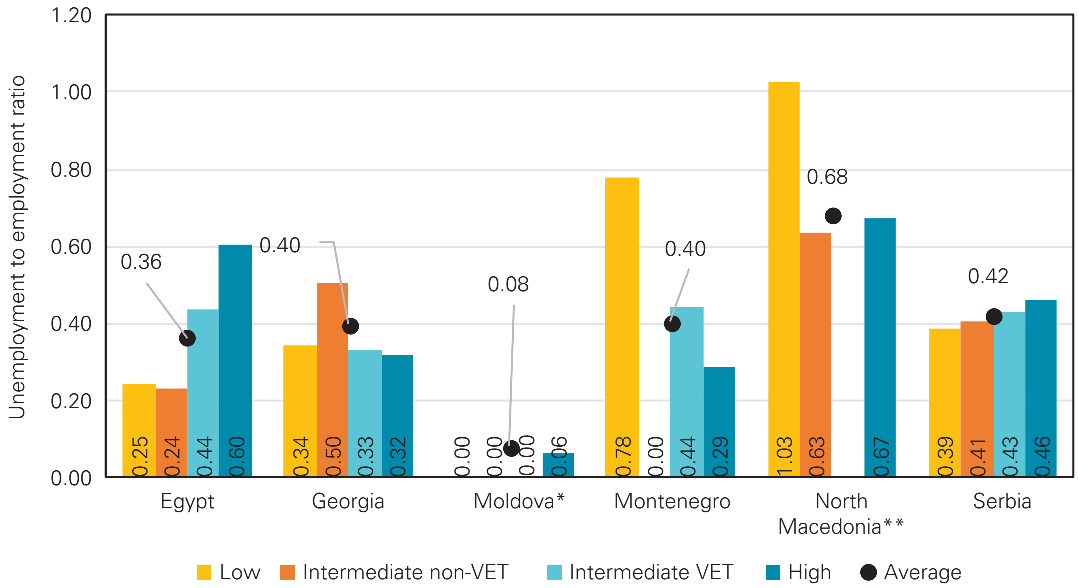
Note: (*) Moldova: 15+ age group; (**) North Macedonia: Data does not allow us to identify VET education levels; (***) Serbia: 15–59 age group
Source: Authors' calculations based on national LFS

Figure 4.7 Women – Unemployment to employment ratio by educational attainment level (15–64 age group), 2016



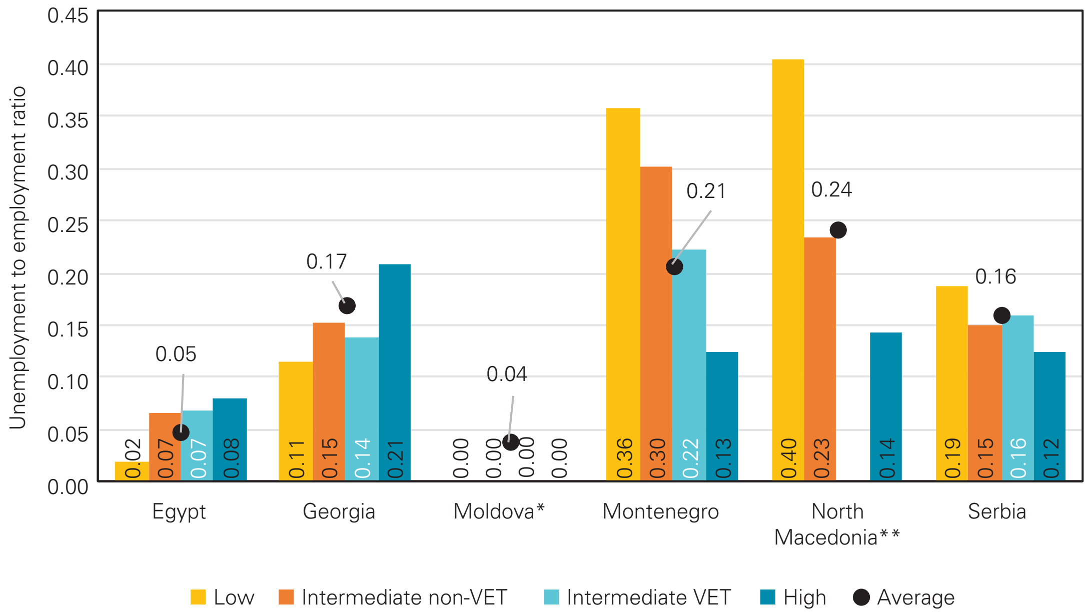
Note: (*) Moldova: 15+ age group; (**) North Macedonia: Data does not allow us to identify VET education levels; (***) Serbia: 15–59 age group
Source: Authors' calculations based on national LFS

Figure 4.8 Unemployment to employment ratio by educational attainment level (15–29 age group), 2016



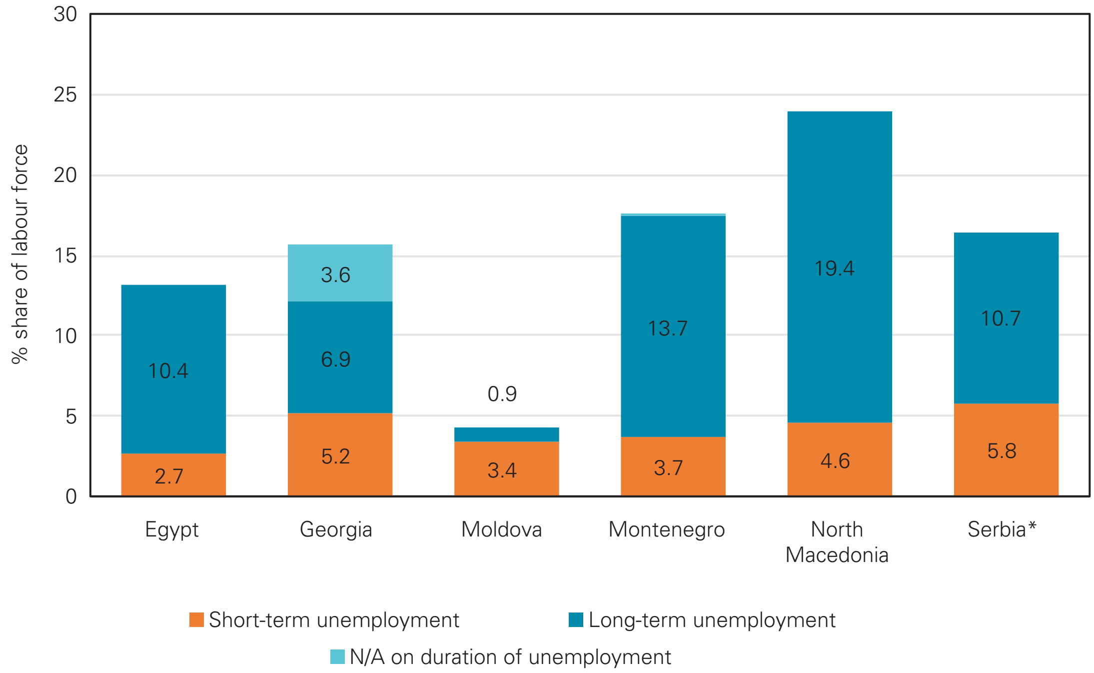
Note: (*) Moldova: Low number of observations; (**) North Macedonia: Data does not allow us to identify VET education levels.
Source: Authors' calculations based on national LFS

Figure 4.9 Unemployment to employment ratio by educational attainment level (30–54 age group), 2016



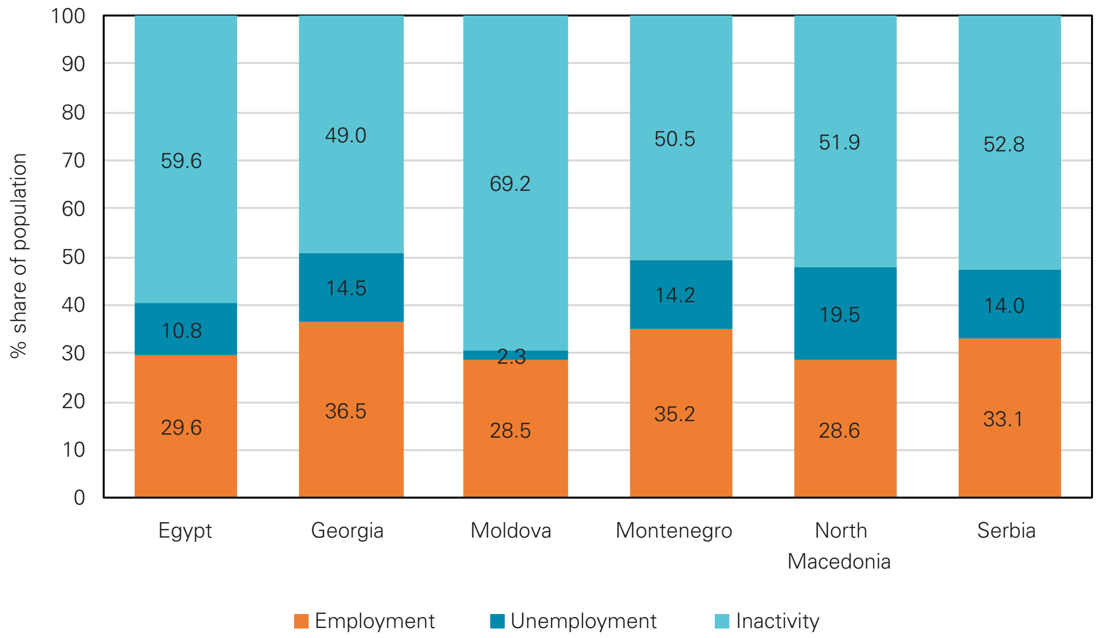
Note: (*) Moldova: Low number of observations; (**) North Macedonia: Data does not allow us to identify VET education levels.
Source: Authors' calculations based on national LFS

Figure 4.10 Unemployment rates by duration of unemployment (15–64 age group), 2016



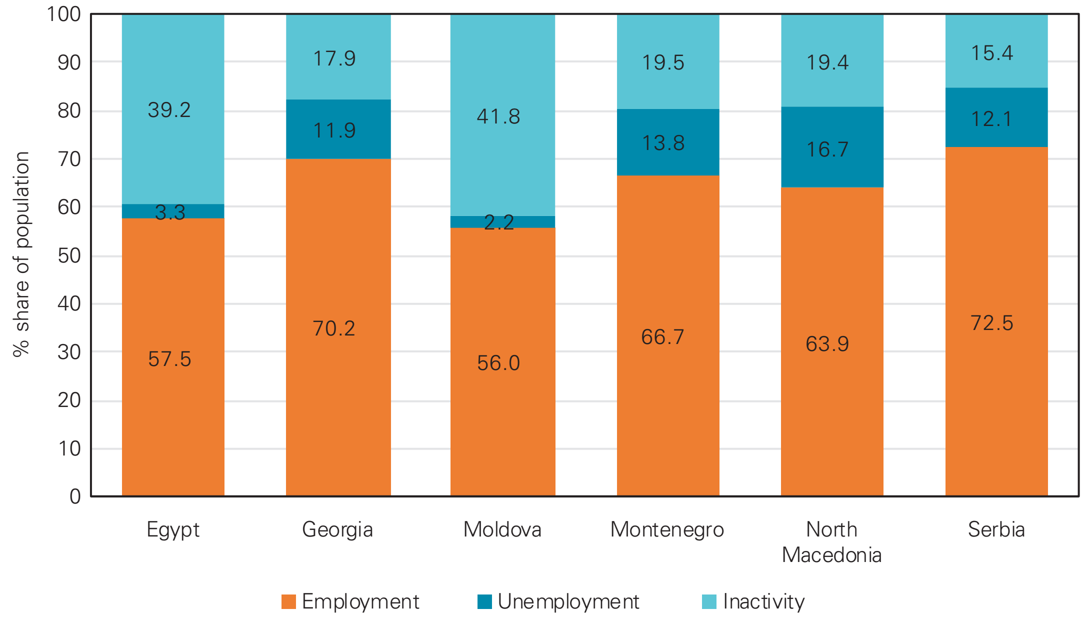
Note: (*) Serbia: 15–59 age group
Source: Authors' calculations based on national LFS

Figure 4.11 Population (15–29) by activity status, 2016



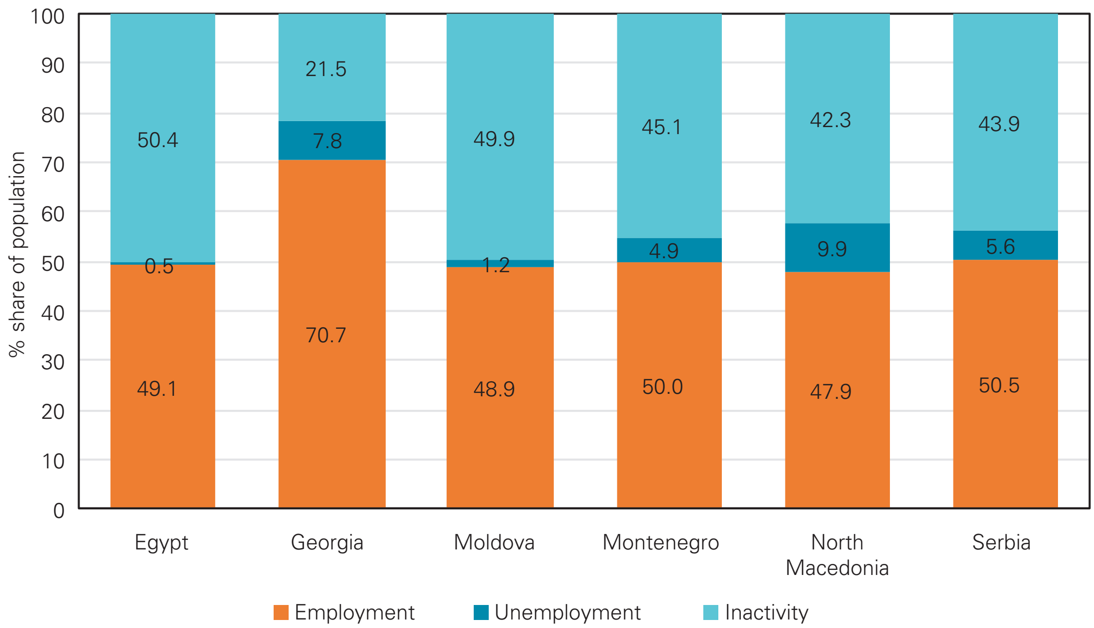
Source: Authors' calculations based on national LFS

Figure 4.12 Population (30–49) by activity status, 2016



Source: Authors' calculations based on national LFS

Figure 4.13 Population (50–64) by activity status, 2016



Source: Authors' calculations based on national LFS

Young people (15–29 years) report relatively low levels of employment and high levels of 'inactivity'. They also account for a sizeable share of unemployment. While employment and unemployment should be taken at face value, inactivity hides several aspects. On the positive side, it includes people who are still in education. This is likely to account for a sizeable part of all inactivity in this age group, as education is often the main activity, especially of the younger part of this age group. On the negative side, inactivity can also be a reaction to not finding suitable employment. The same holds true when the process of entering the labour market is difficult or the person has to go through secondary, unofficial labour markets. Ideally, this group is also analysed using the NEET indicator. This can help to disentangle the positive aspect of enrolment in education from the negative aspect of inactivity. The higher unemployment rates among young people hint at difficulties in the school-to-work transition.

The mid-age population show the highest levels of employment, inactivity is lowest in all countries for this group. It is especially low in countries where women tend to participate more in the labour market (Georgia, Montenegro, North Macedonia and Serbia), while it is higher in those countries where the participation of women is lower (Egypt and Moldova). Unemployment rates in this part of the population range from 2.2% in Moldova and 3.3% in Egypt to 16.7% in North Macedonia. However, it should be noted that inactivity is likely to hide some form of unemployment in countries with low unemployment rates. For example, unemployment is much lower in Egypt among the prime-age labour force, and, to a lesser degree, in Georgia. However, if we include inactivity, the Georgian situation looks much better than the Egyptian one. This probably reflects the higher participation rate of women in the Georgian labour market relative to the Egyptian labour market[16].

The oldest age group shows typical diminishing of the activity rate and hence diminishing unemployment and employment rates. In the group aged 50 and above, early retirement and temporary withdrawal from the labour market are typical features, especially when workers are confronted with job losses.

In terms of possible policy messages, this evidence suggests that much more needs to be done to support young people in finding their first job. Furthermore, given the multiple transitions, much more needs to be done to support adults in upward transitions during their career or when moving from job to job. The implication would be to consolidate specific services offered by intermediation bodies, such as the public employment services, career guidance offices and private providers of employment services. It would also mean teaching flexibility and resilience as core skills at school and providing young people with access to reskilling mechanisms.

4.2.2 (Young people) not in employment, education or training (NEET)

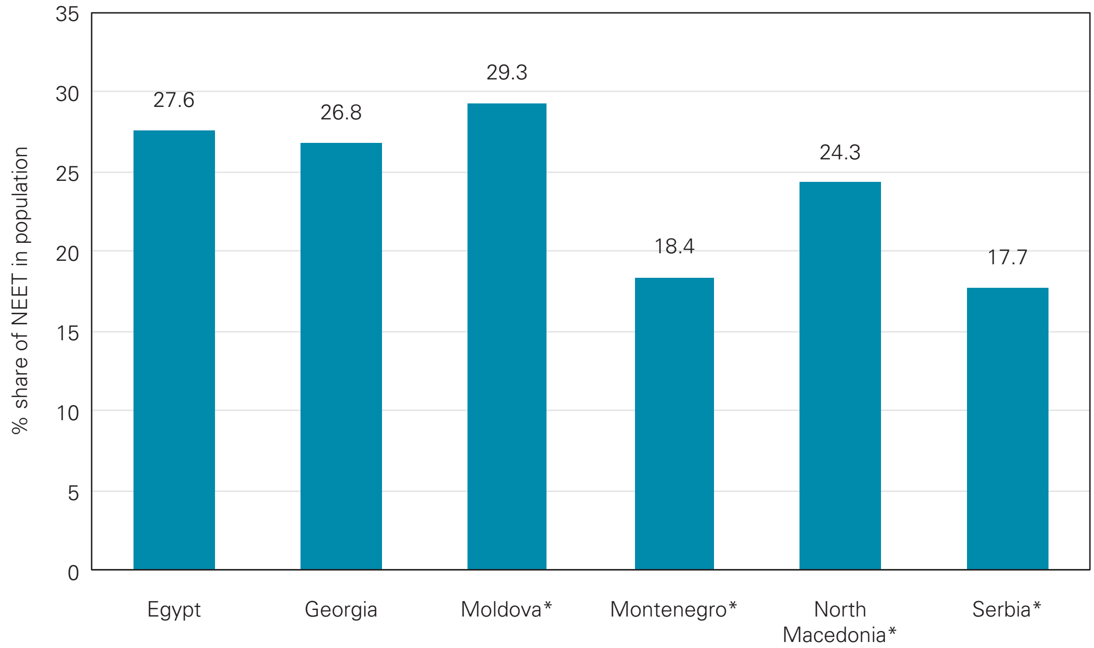
> This methodology calculates the rate of young people who are not in employment, education or training. The underlying reason is presumed to be some form of mismatch, as those who are not in education are generally presumed to have finished their education and should have found employment in some form. It thus combines non-participation and unemployment.

The situation of young people in the labour market can be better analysed by concentrating on NEETs, the share of young people who are not in employment, education or training. Figure 4.14 provides these rates for all six countries. The highest rate can be found in Moldova (29.3%) followed by Egypt (27.6%), Georgia (26.8%) and North Macedonia (24.3%). Montenegro (18.4%) and Serbia (17.7%) manage to stay below 20%. In Georgia and Egypt, access to LFS data allowed us to identify school attendance directly. This data is needed to break down the inactive part of the labour force into those who are inactive because of education or training attendance and those who are not. In terms of interpretation, this indicator should be as low as possible, as it reflects people who are already inactive in the labour market, corrected for educational activity. In the other four countries, we had to rely on data provided by the ETF (KIESE dataset – key indicators on education, skills and employment).

It is worth noting that NEETs are a very heterogeneous group (combining multiple groups such as those who are unemployed for short or long periods or inactive individuals, who in turn reflect multiple social groups such as young women with family care obligations, low-skilled or over-qualified young people, vulnerable young people, or those residing in rural or underdeveloped regions). To make meaningful policies, there is a clear need to calculate

16 As the background report for Egypt also notes, the distinction by gender in Egypt is extremely important in analysing the labour market.

Figure 4.14 Young people (15–24) not in employment, education or training, 2016



Sources: Authors' calculations based on national LFS; (*) ETF KIESE data

in each country the incidence of the different subgroups and the causes of their exclusion (ETF, 2015).

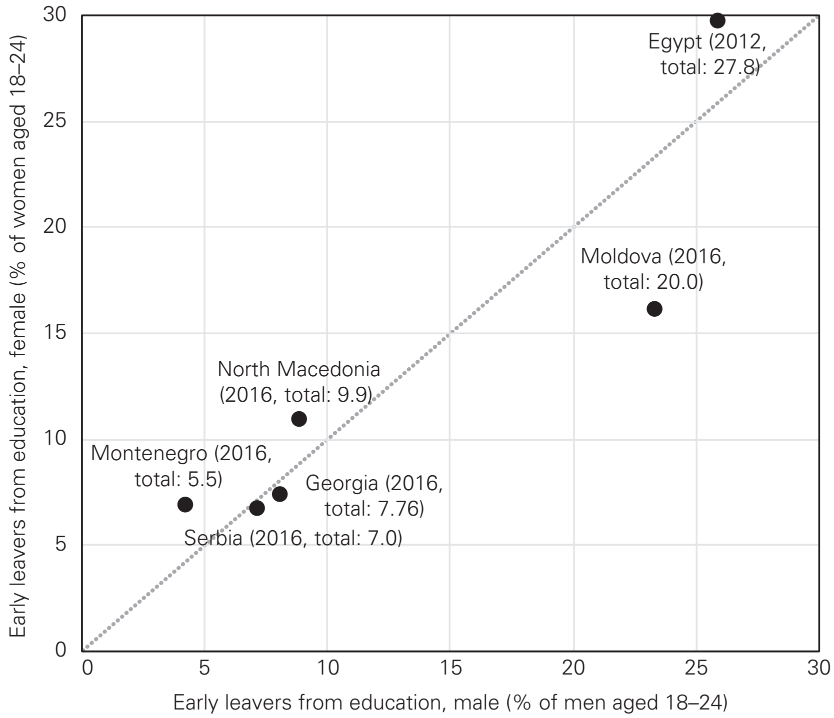
In the underlying Egyptian and Georgian microdata, we can see relatively low rates (for the country) of inactivity among the younger part of this age group, the 15 to 19-year-olds. This indicates that a large proportion of that age group is in education. Over time (between 2008 and 2014 in Egypt; between 2012 and 2016 in Georgia), the trend is positive: there is a significant reduction in this rate from 18.2% to 14.2% in Egypt and from 19.7% to 16.4% in Georgia.

To understand the differences between the countries, three additional figures provide information on the percentage of early school leavers (Figure 4.15), tertiary education attainment (Figure 4.16) and share of VET education (Figure 4.17). All elements can have an influence on the transition process and the labour market experience of young people. The first two graphs show the shares for women (vertical axis) and men (horizontal axis) and provide some insight into the differential outcomes by gender.

Figure 4.15 shows the percentage of early school leavers. Positioning towards the upper right thus show the highest incidence of early school leavers. This applies to Egypt, which has a total of 27.8% of early school leavers, with women accounting for a slightly higher share than men. This is, of course, likely to feed into Egypt's high NEET rates. It is then no surprise that the second-highest level can be found in Moldova, with 20%, where men have a higher tendency to become early school leavers. This corresponds to the high NEET rate in Moldova. All other countries show rates below 10%, with only a few differences between men and women.

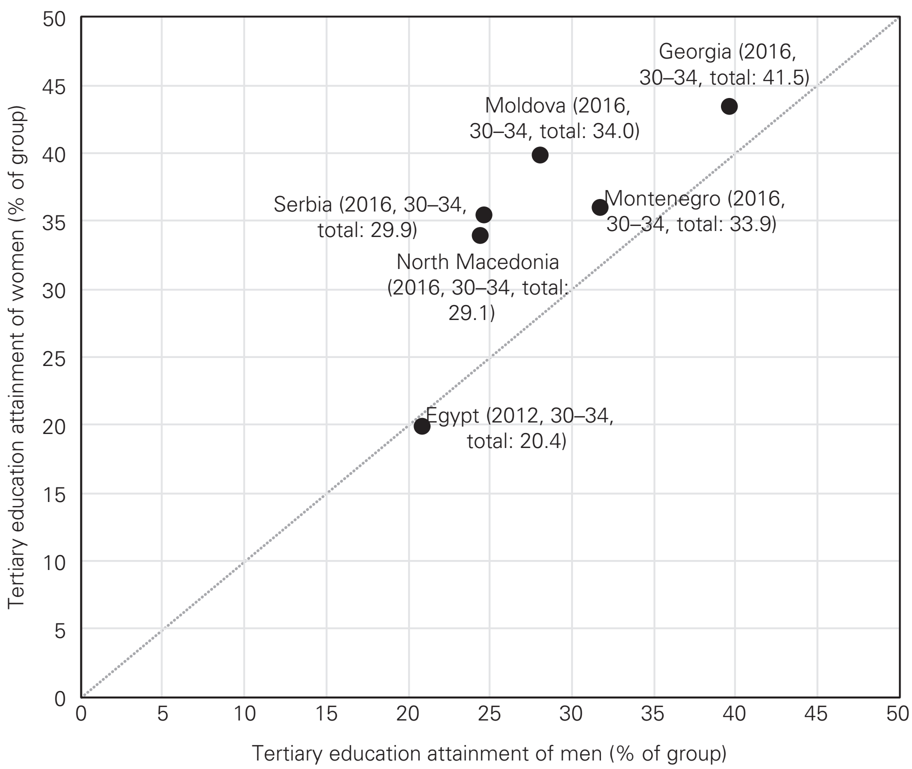
Figure 4.16 shows the share of men and women aged 30 to 34 attaining tertiary education. Here, Georgia stands out positively with 41.5% attaining tertiary education. This is followed by Moldova, Montenegro, Serbia and North Macedonia. Egypt exhibits much lower rates with an average of 20.4% in 2012. The high rates are especially supported by the tertiary attainment of women, which tends to be higher in all countries except Egypt. The difficulty in finding work in Georgia, despite the high level of education, points towards the problem that the qualifications obtained do not match the skills required in this and many other countries. This is often also due to a lack of work opportunities at a higher level, which will be revisited in the context of occupational mismatch.

Figure 4.15 Early school leavers by gender (%)



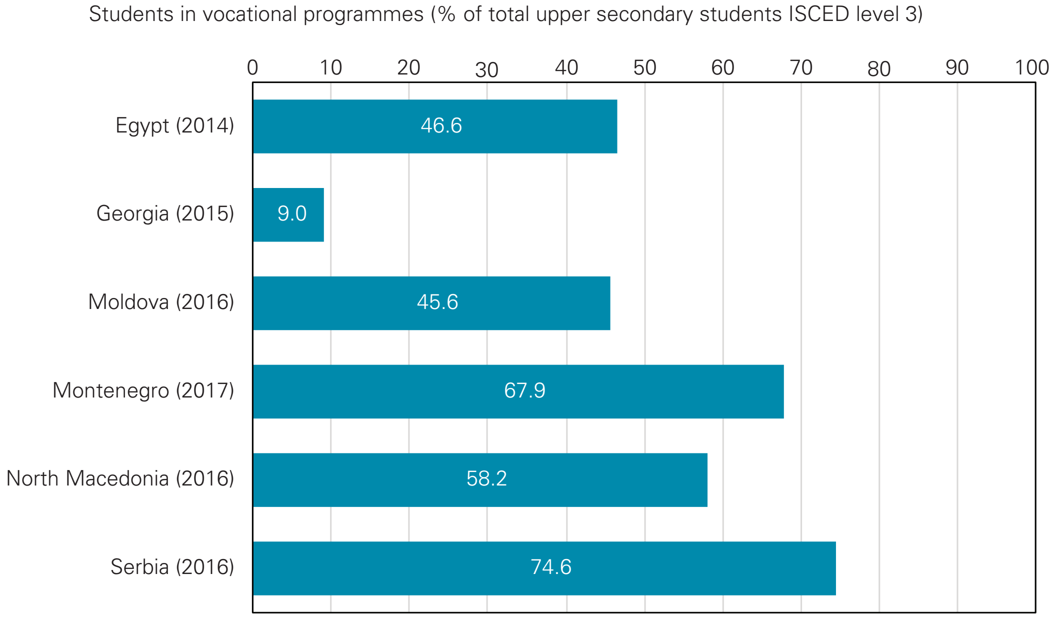
Source: ETF KIESE data

Figure 4.16 Tertiary education attainment by gender (%)



Source: ETF KIESE data

Figure 4.17 Students in vocational programmes



Source: ETF KIESE data

Ideally, vocational programmes can 'build a bridge' between the skills that are taught and those that are in demand as the programmes are specifically geared towards specific occupations. The usage and acceptance of vocational programmes differ, just as their success in actually matching the skills taught to the local labour market situations also varies. Figure 4.17 shows the share of upper secondary students in vocational programmes. Note that the context, the setting and the practical skills taught might be quite heterogeneous across the countries. They might also have different goals: either specifically preparing students for final occupations or providing a general education that also includes practical elements. Here, Georgia has a strikingly low percentage of vocational programmes. In the other five countries, about half or more of all secondary students follow some vocational programme.

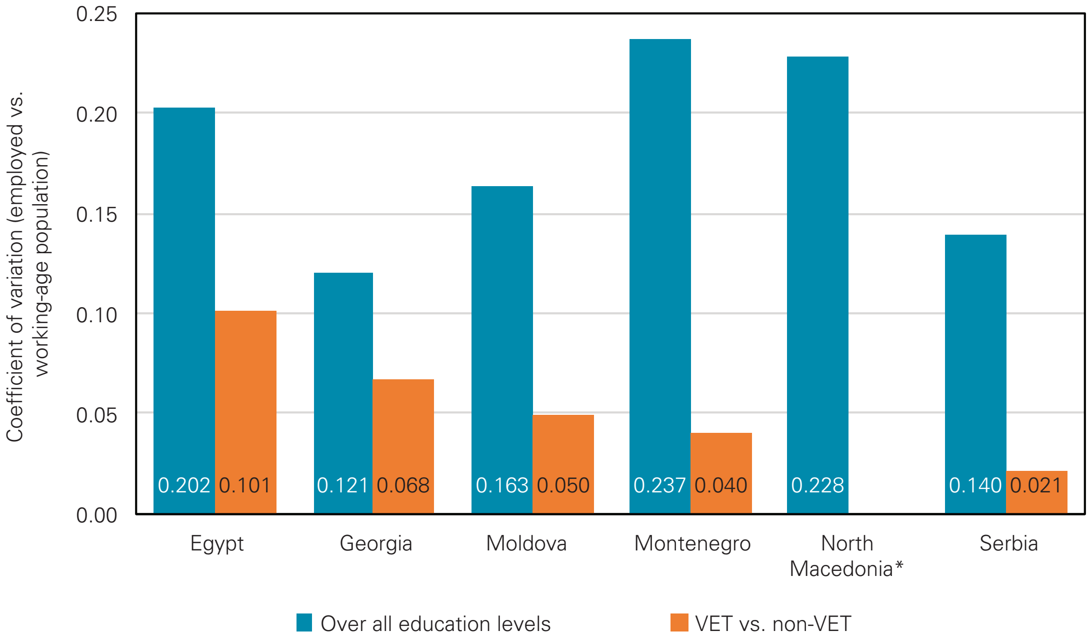
4.2.3 Coefficient of variation by skills

This indicator compares the distribution of skills within different groups while correcting for the overall size of the underlying statistic. The difference in skill composition of employed to working-age population[17] is expressed in just one number, which measures the overall extent of mismatch. The higher the number, the greater the difference between the skills possessed by people employed in the labour market and the skills possessed by the working-age population. The extent to which the distributions are different can therefore be interpreted as a measure of the ineffectiveness caused by the matching process of supply and demand of skills in the labour market.

This is a standardised indicator of variation across the two groups employed versus working-age population. Figure 4.18 shows the variation in the two groups – employed people and the full working-age population – for various education levels. In other words, higher coefficients imply that employed people differ in their distribution across the education levels relative to the working-age population. The graph first distinguishes the variation across all education levels. It then analyses the differences between VET-educated versus non-VET-educated. A value close to zero would thus imply that the share

[17] The decision to use working-age population data instead of unemployment data was taken due to data limitations (e.g. Moldova has almost no unemployment but a high level of inactivity).

Figure 4.18 Coefficient of variation (15–64), 2016



Note: (*) North Macedonia: Data does not allow us to identify VET education levels.
Source: Authors' calculations based on national LFS

of education (or VET versus non-VET) of employed people is virtually the same as that of the population. The higher the value the more differences there are among the groups identified.

Across all education levels, the indicators in North Macedonia, Montenegro and Egypt suggest stronger differences in the level of employment of those with specific qualifications versus those in the overall population. In other words, higher levels of qualification improve labour market opportunities in these countries in particular. This is also true in Moldova and Serbia, and to a lesser degree in Georgia, where the educational mix of those employed differs less and less from the educational mix of the overall population. While the indicator does not imply high or low levels of employment (or unemployment), it simply shows how different the outcomes in the labour market are for different groups. The impact of VET training on the overall variation is usually rather small.

In Egypt and Georgia is a sizeable share of the differences also to be found in the inherently more aggregated version comparing VET-trained people with non-VET educated people. In Moldova and Montenegro, there seem to be some differences, but they are a relatively minor share. In Serbia, there is almost no difference.

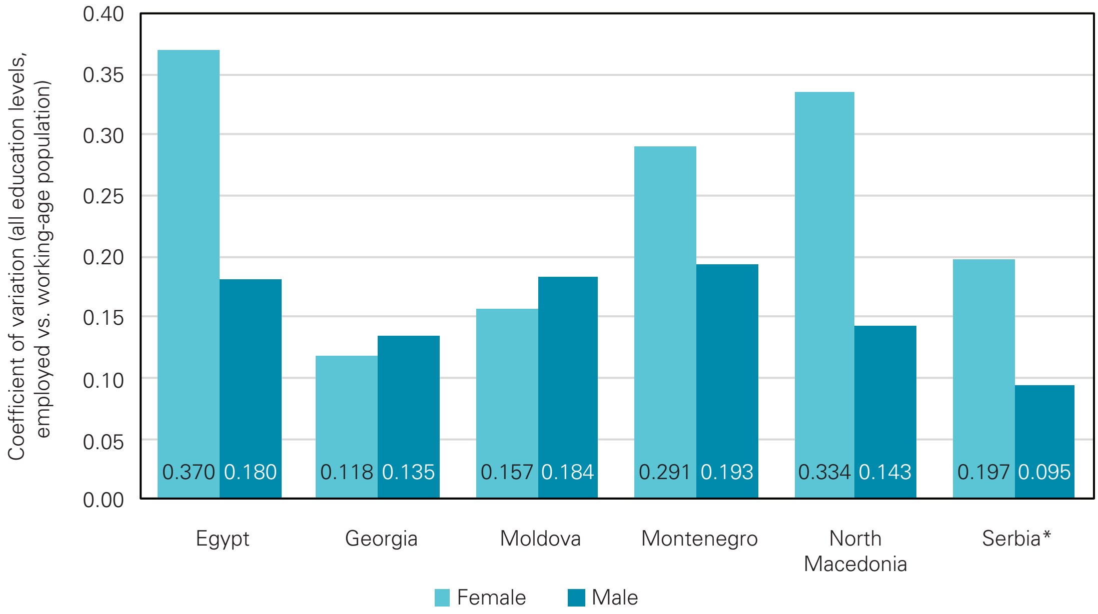
Figure 4.19 shows the differences by gender. In Egypt, but also in Montenegro, North Macedonia and Serbia education matters more for the labour market outcomes of women than for men. The opposite is true in Georgia and Moldova, albeit the differences are very small here.

4.2.4 Variance of relative unemployment rates (by education level)

This indicator shows how unemployment deviates within education levels from the average of the entire country. The higher the value of the variance, the higher the level of mismatch. While education levels are generally used as in our indicator, the methodology would also be applicable to subgroups such as age, age and gender, and (previous) occupation.

The variance of relative unemployment rates is a similar measure to the coefficient of variation. It

Figure 4.19 Coefficient of variation by gender (15–64), 2016



Note: (*) Serbia: 15–59 age group
Source: Authors' calculations based on national LFS

measures the deviation by education level from the average unemployment rate within the country. Here we find rather low measures for Georgia, Serbia and Moldova, while North Macedonia, Egypt and Montenegro show high values. In Serbia and Georgia, we can see that these low skills mismatch indicators can coincide with rather high unemployment rates. In these cases, unemployed people are rather comparable to the overall population, which would hint at an overall shortfall of demand rather than a specific skills mismatch, such as a situation when job seekers' skillset does not match demand.

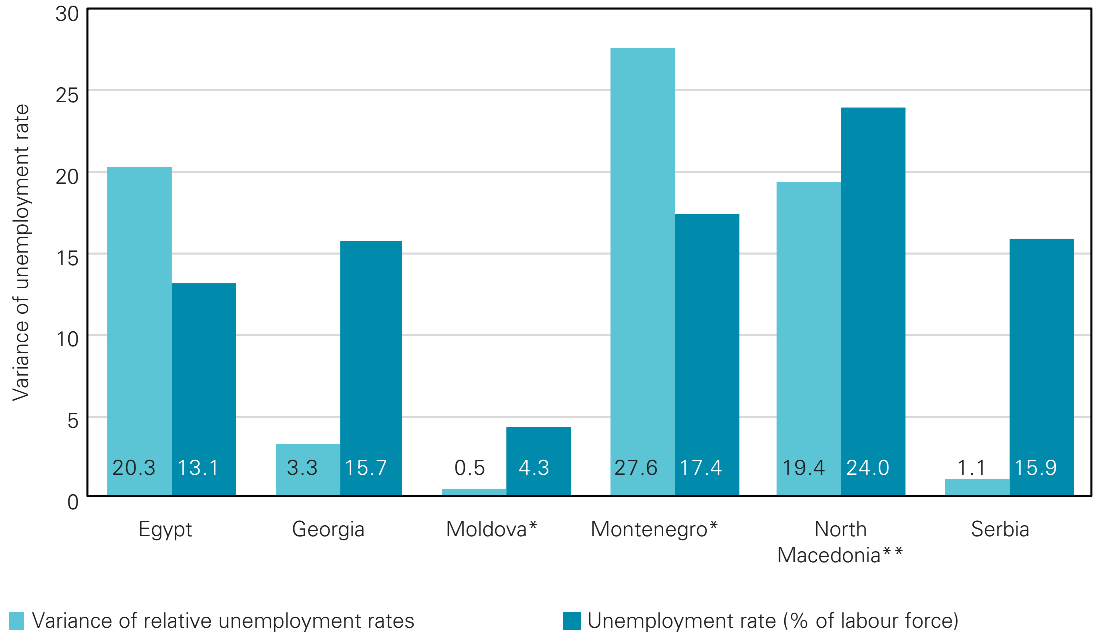
It is essential to analyse such variance of relative unemployment by education in order to identify more clearly the reasons behind high incidence of unemployment and low aggregate demand than the gaps in educational attainment or skills versus employment demand. Policy measures vary greatly if one or another reason causes a high incidence of unemployment. Such policy support should focus on raising the education and/or skill level or the motivation of job seekers to take up jobs (generally classified as policy approaches to boost employability of workforce) or remove barriers to activation/employment (see impact of cultural norms or unavailability of social services upon gender employment gaps). In contexts of low demand, different strategies are needed, e.g. integrated approaches to economic and regional development, innovation, technology boost, structural reforms and new impetus to trade and exports.

4.2.5 Relative wages

This methodology compares wages across education levels over time, either relative to a benchmark wage or indexed vis-à-vis a base year. It can usefully be plotted in a diagram, as it is then very easy to see how certain education levels are better remunerated than others over time. An education level that is seen to attract a higher income than that achieved by people with other levels of education can thus be a sign that this level of education is in higher demand in the labour market.

Using wages and wage developments to analyse skills mismatch provides a very mixed outcome. No strong conclusion could or should be drawn for the limited period observed and for the few countries that were studied in this report. While all the

Figure 4.20 Variance of relative unemployment rates (15–64), 2016



Notes: (*) Aggregated from five-year age groups – high number of missing values due to small cell size; (**) Variance over three education levels (low, intermediate, high) instead of four (low, intermediate non-VET, intermediate VET, high) due to data limitations.
Source: Authors' calculations based on national LFS

countries show that higher level of education results in higher levels of income, wage developments that show shifts in the supply versus demand imbalances do not show a very explicit picture. A human capital wage regression approach might have to be taken to tease out specific effects that are due to institutional setting, sluggish adjustment of wages to demand and supply imbalances. In such an approach, additional factors could be taken out in order to understand better how skills are rewarded in the various national labour markets. This would, however, require microdata and would go beyond the scope of the current exercise.

As shown in Table 4.1, the highest (annualised) wage growth rates can be found at almost any education level. In Georgia, the lowest level exhibits the strongest annual growth, which was explained in the national report more as a catch-up wage development rather than an identification of specific shortages. In Egypt, the strongest increase can also be found in the wages earned by people with a low level of education, but there is little difference between all the four observed qualification levels, and the ordering shifted over the observed years.

In Moldova, people with secondary professional training experienced the biggest changes in annual wages, while in Serbia people with the lowest level of education showed experienced the highest annualised growth in wages, again without great divergences across education levels.

4.2.6 Occupational mismatch

This method is based on comparisons of the ratio of people with a given education level (ISCED) working at an inappropriate skill level (measured by the International Standard Classification of Occupations – ISCO) to all workers within that ISCED level.

Within the occupational mismatch and over- or under-education the view or angle taken by the indicator differs. By definition of ISCO, some level of qualification is assigned to occupations, here by ISCO 1-digit groups, are assigned.

The degree to which persons are employed in occupations below (not requiring) their level of

Table 4.1 Wages by education level

Country	Education level	Period	Average annual change in %
Egypt (15–64 age group)	Low	2012–16	25
	Intermediate non-VET		17
	Intermediate VET		19
	High		13
	Average		18
Georgia (15–64 age group)	Low	2012–16	27
	Intermediate non-VET		9
	Intermediate VET		12
	High		9
	Average		10
Moldova (15–64 age group, single households only)	Gymnasium	2012–16	2
	Secondary school		6
	Secondary professional		9
	Secondary specialised		9
	Higher		7
	Average		6
Serbia (15–59 age group)	Low	2014–16	6
	Intermediate non-VET		5
	Intermediate VET		3
	High		4
	Average		5

Source: Authors' calculations based on national LFS

education is given in Table 4.2. It is split into elementary occupations – for which everybody with secondary education is considered 'mismatched' or over-qualified, and semi-skilled occupations where tertiary education is, by assumption, presumed to be over-qualified and thus mismatched.

The total mismatch in elementary occupations goes from 7.1% in Serbia, through Montenegro (7.4%), Georgia (9.4%), Egypt (10.4%) to 13.9% in North Macedonia and 14% in Moldova. North Macedonia and Moldova thus effectively have twice as many people with an intermediate level of education employed in elementary occupations than Serbia. With the exception of Georgia, the three other countries that can provide these figures also by gender all show a higher mismatch for women than for men among the elementary occupations.

In the case of semi-skilled occupations, occupational mismatch is even more diverse among the countries examined (Table 4.3). Montenegro has the lowest level of mismatch with 14.2% of people with higher level of qualification than required. The figure for Egypt is 18.7%. In North Macedonia and Moldova, more than one in five people working in a semi-skilled occupation have tertiary education (21.7% and 21.8%, respectively). The figure for Serbia is close to a quarter (24.2%) and Georgia shows the highest level with 36.1%, more than one-third. The differences by gender are clear-cut: women with a high level of qualifications are less likely to be mismatched than

Table 4.2 Occupational mismatch – People with upper secondary education working in elementary occupations, 2016 (% of all people with upper secondary education)

	Egypt (15–64)*	Georgia (15–64)*	Moldova (15–64)**	Montenegro (15–64)**	North Macedonia (15–64)**	Serbia (15–59)**
Total	10.4	9.4	14.0	7.4	13.9	7.1
Male	9.2	10.4	–	5.4	12.4	–
Female	17.2	7.9	–	10.9	16.6	–

Notes: (*) Only people not in education. (**) People in education and not in education.
See www.oecd-ilibrary.org/education/education-at-a-glance-2010/education-and-occupational-mismatches-for-young-individuals-2003-2007_eag-2010-table175-en
Source: Authors' calculations based on national LFS

Table 4.3 Occupational mismatch – People with tertiary education working in semi-skilled occupations, 2016 (% of all people with tertiary education)

	Egypt (15–64)*	Georgia (15–64)*	Moldova (15–64)**	Montenegro (15–64)**	North Macedonia (15–64)**	Serbia (15–59)**
Total	18.7	36.1	21.8	14.2	21.7	24.2
Male	22.9	46.2	–	16.5	22.9	–
Female	9.8	26.6	–	12.2	20.6	–

Notes: (*) Only persons not in education. (**) Persons in education and not in education.
See www.oecd-ilibrary.org/education/education-at-a-glance-2010/education-and-occupational-mismatches-for-young-individuals-2003-2007_eag-2010-table175-en
Source: Authors' calculations based on national LFS

men. Georgia shows significantly less mismatch for women (26.6% versus 46.2% for men), in Egypt the share for women is also only half of that for men, while in Montenegro the difference is still sizeable but not as big, whereas women fare just marginally better in North Macedonia.

There are many reasons to explain such a high incidence of occupational mismatch for people with tertiary attainment, and to lesser extent for those with secondary level education. Probably the main reason is that economies do not create high-end jobs quickly enough to satisfy the level of new entrants in the market, as all the selected countries experienced a constant increase in university enrolment and graduation in recent years. This raises the issue of underutilisation of human capital and the increased risk of migration and brain drain. It also calls for a more sophisticated approach to addressing emerging mismatches. This would entail, for example, not only the acquisition of more relevant skills in schools and better career orientation, but also the stimulation of value-added economic activities, requiring higher levels of qualifications. The precarious transition experienced by young people when they move from school to work (as revealed in ILO school-to-work transition surveys, for example) should also be noted. Many young people choose to take up jobs below their level of education or qualification as a strategy to gain work experience, a 'must-have' in the eyes of many employers (as schools often do not equip graduates with the necessary practical or soft skills needed in the workplace). While understandable as a short-term strategy to access employment, a mismatched job comes with a wage penalty, frustration and skills depreciation. Finally, another trigger factor is the way in which the workforce looks for jobs in developing and transition countries. Public employment services have a limited outreach and play a limited role in job matching. Most people prefer to seek employment through a network of family and friends. Geographical internal mobility is quite low and therefore the variety of job opportunities people can access is rather limited.

4.2.7 Over- and under-education

This method can be used in cases where datasets do not include specific questions on over-education or over-skilling; it is nevertheless quite a simplistic measurement and must be interpreted as a proxy. The empirical method is a purely statistical measure where the distribution of education is calculated for each occupation; over-education is defined as existing when the level of education is more than one standard deviation above the mean or above the mode for the education level for a given occupation. The educational mean and/or mode for each occupation is thus assumed to be a match for that occupation, but this may very well be a false assumption. In theory everybody employed in a given occupation could be mismatched.

In our context, the distribution of education is calculated for each occupation group, where over-education is defined as existing when the level of education is more than one standard deviation above the mean. The model calculation is based on the level of education measured by the national classification of education. Only the two countries with microdata (Egypt and Georgia) are directly comparable (Table 4.4). We had to rely on aggregate data for the other countries, which allows only for a calculation by proxy.

Over-education can be found predominantly among the elementary and intermediate occupations. In Egypt, the highest proportion can be found within the elementary occupations, followed by clerks, skilled agricultural and fishery workers and, somewhat surprisingly, ISCO group 1 (legislators, senior officials and managers). This last group is likely to be an artefact of the empirical method, in this context it may be the result of a significant share of people with a low or intermediate level of qualification in the occupation. This would push down the empirically determined, implied qualification requirement. That is the weakness of the empirical method especially in occupations in which the qualification levels can be quite heterogeneous, where the group is small, or when the identification of qualifications is imperfect. This problem is amplified in the countries where we do not have microdata (Table 4.5). As a result, over-education cannot be identified in many cases, e.g. Montenegro. This should not be interpreted to mean that there is no over-education in Montenegro, it simply cannot be identified with the given data using the empirical method. We know from the occupational mismatch indicator that there are over-qualified people in elementary and semi-skilled occupations in Montenegro (see Tables 4.2 and 4.3). In general, it can be said that the empirical method works less well if no (real) microdata is available, thus both Tables 4.5 and 4.6 should be seen as an indication that potential over- and under-education exists in these four countries.

In Georgia, over-education is strongest among technicians and associate professionals as well as clerks, and, to a lesser degree, service workers, followed by lower level occupations: plant and machine operators and elementary occupations. Among the first two groups mentioned here, more than one-third of the occupations are filled with over-qualified workers. In the other two groups, between one-quarter and one-fifth of the people are considered over-qualified.

Based only on the aggregate data, Serbia has most over-qualification in the service occupations, followed by the lower level occupations. Note that the percentage should not be compared to Egypt or Georgia as those are calculated using microdata.

It is striking to see that in several intermediary occupations where over-education is observed that under-education is identified using the empirical method. In Georgia, this can be seen in the case of clerks and technicians, while in Egypt, legislators and managers are also identified. It seems odd in this context to see an elementary occupation identified as having a high share of under-education, but that is likely to be an artefact of having a significant share of over-qualified personnel in the occupation.

Over-education can be found across all countries among service and sales workers, in agricultural occupations and, of course, in elementary occupations. In some occupations, more than a quarter of the workers are considered over-qualified. Under-education – which is not likely to be an artefact of the method – can be found among clerks and also technicians and associate professionals. Under-education is less likely to occur in occupations where there are mandated qualification requirements (e.g. nurses, doctors, accountants).

Overall, the empirical method seems to be dependent on the availability of microdata, ideally with a detailed level of qualifications and occupations. If several data waves of a country can be combined to determine the average qualification requirement, artefacts of the data are less likely to appear. It shows, however, how data-hungry this indicator is, and how difficult it probably is to identify a dynamic development of over- and under-education in a national labour market.

Table 4.4 Occupational mismatch – Over- and under-education calculated from microdata (15–64 age group), 2016 (% share of workers in an occupation)

ISCO 88	Over-education		Under-education	
	Egypt	Georgia	Egypt	Georgia
01 Legislators, senior officials and managers	20.9	1.9	33.0	8.9
02 Professionals	3.5	1.5	11.6	2.8
03 Technicians and associate professionals	29.5	0.0	6.6	13.1
04 Clerks	27.5	0.0	9.5	23.7
05 Service workers and shop and market sales workers	11.7	30.5	26.6	2.0
06 Skilled agricultural and fishery workers	31.7	11.4	37.6	8.1
07 Craft and related trades workers	5.7	16.1	33.1	3.6
08 Plant and machine operators and assemblers	6.5	25.7	29.6	1.7
09 Elementary occupations	31.7	19.1	29.6	6.7

Note: Calculated from microdata
Source: Authors' calculations based on national LFS

Table 4.5 Occupational mismatch – Over-education calculated from aggregate data (15–64 age group), 2016 (% share of over-educated workers among workers in an occupation)

ISCO 08	Moldova	Montenegro	North Macedonia	Serbia*
01 Managers	0.0	0.0	0.0	0.0
02 Professionals	0.0	0.0	0.0	0.0
03 Technicians and associate professionals	0.0	0.0	0.0	0.1
04 Clerical support workers	0.0	0.0	0.0	1.5
05 Services and sales workers	13.7	0.0	0.0	7.1
06 Skilled agricultural, forestry and fishery workers	3.4	0.0	4.3	3.8
07 Craft and related trades workers	6.0	0.0	3.8	2.3
08 Plant and machine operators and assemblers	4.1	0.0	5.1	2.3
09 Elementary occupations	6.5	0.0	2.6	3.4

Notes: (*) Serbia: 15–59 age group; calculated from aggregate data
Source: Authors' calculations based on national LFS

Table 4.6 Occupational mismatch – Under-education calculated from aggregate data (15–64 age group), 2016 (% share of under-educated workers among workers in an occupation)

ISCO 08	Moldova	Montenegro	North Macedonia	Serbia*
01 Managers	6.2	0.0	4.6	1.1
02 Professionals	2.0	0.0	0.2	0.8
03 Technicians and associate professionals	8.3	5.7	0.8	0.0
04 Clerical support workers	7.1	0.0	2.4	2.3
05 Services and sales workers	0.1	3.5	11.6	0.3
06 Skilled agricultural, forestry and fishery workers	0.6	0.0	0.0	0.2
07 Craft and related trades workers	0.1	10.1	0.0	0.1
08 Plant and machine operators and assemblers	1.5	8.8	0.0	0.0
09 Elementary occupations	2.1	0.0	0.0	1.1

Note: (*) Serbia: 15–59 age group; calculated from aggregate data
Source: Authors' calculations based on national LFS

5. CONCLUSIONS AND RECOMMENDATIONS

We developed a system in this project to systematically collect and harmonise data on skills mismatch in ETF partner countries. This was piloted using several different labour market and skills mismatch indicators in seven countries: Georgia, Egypt, Serbia and Morocco in a first round, with Moldova, Montenegro and North Macedonia added in a second round.

The process that was developed allows for the indicators to be easily updated, given the availability of data in the form of microdata (Egypt, Georgia) or aggregated tables according to the data collection template (Serbia, Moldova, Montenegro and North Macedonia). In the case of Morocco, data availability or accessibility meant we could only calculate a few indicators and sometimes these were adapted or proxied indicators. The Moroccan results were therefore largely excluded in the discussion of this report.

Using the experience from the pilot countries, we summarise the advantages and disadvantages of the indicators in Table 5.1. We recommend calculating the set of indicators for which there is generally sufficient, easily interpreted data available. We would count unemployment rates (or ratios), NEET indicators and the coefficient of variation by skills in this group. Occupational mismatch, if calculated pragmatically as in this report, should also be calculated. Here, pragmatism by virtue of its definition might lead to less clear-cut results and might come at the cost of cross-country comparability, but it provides an additional and important angle, while its calculation is not overly complicated or demanding on the data.

However, only looking at unemployment in a cross-country comparison is misleading, as the number of unemployed people depends heavily on the services provided by the national unemployment protection system. In some countries, unemployment is 'hidden' within underemployment or inactivity. It is therefore important to also look at non-worker ratios or NEET rates.

We do not recommend comparing the variance of relative unemployment rates across countries, as this type of analysis has unemployment as a stringent concept that might be more important in some countries than in others, while the indicator is strict in only using formal unemployment. However, this indicator might be useful for analysing dynamics within a country given that there are no breaks in the time series of national data.

The coefficient of variation by skills (CVAR) is generally recommended for national mismatch analysis as well as for comparative research. It does not require very detailed data (also due to flexibility), and the indicator's one number contains a lot of information. It might be more difficult to calculate and interpret. We also need to be careful in interpreting the results across countries if education levels (definitions and /or categories) differ.

Indicators using relative wages are generally recommended if there is reliable data on wages. They are easy to interpret, easy to calculate and are generally well understood in the country context. Additional information to make wages comparable, e.g. purchasing power parity, would be useful for comparative research and cross-country analysis.

The indicators for occupational mismatch proved quite useful. Their calculation and use would therefore be generally recommended. While the original OECD definition requires a high level of detail (it only covers the 25–29 age group) that might not be available in smaller countries due to data issues (low number of observations). The more pragmatic approach chosen in this report might be useful in many countries. The definition can be adapted by extending the age group (as we did to increase the number of observations), but it changes the message of the indicator.

The empirical method is not generally recommended for cross-country comparison. It is only feasible if microdata is available as it does not produce reliable results when calculated using aggregate data. It is highly dependent on how education levels are classified, i.e. it is not feasible if there are only a few education levels, e.g. only three levels. This method will not create any reasonable results, as over- or under-education is measured at an individual level and is based on standard deviation. This measure is too 'rough' for a small number of education levels. In principle, it would also require education levels to be ordinal (from lowest to highest), which is sometimes not easy to accomplish.

Table 5.1 Review of indicators

Indicator	Mismatch analysis (*)	Cross-country comparison (*)	Data requirement	Interpretation/analysis
Unemployment rate	+++	++	Usually in LFS/household survey	Common and easy to interpret Can be misleading as a single source
(Non-)worker/ population ratio	+++	+++	Usually in LFS/household survey	Common and easy to interpret
NEET	+++	++	Usually in LFS Identification of 'in education or training' is less straightforward in some countries	Easy to interpret Crucial to understand the school-to-work transition
Variance of relative unemployment rates	+++	0	Usually in LFS Comparability hinges on unemployment classification (and its importance in the countries' economy)	Very dependent on the classification of education levels Uses only (formal) unemployment
Coefficient of variation by skills (CVAR)	+++	+++	Usually in LFS	Encompassing indicator Somewhat difficult to calculate and interpret
Relative wages	++	+	Requires reliable wage data Additional data for cross-country comparison	Simple indicator Relatively easy to interpret
Occupational mismatch	++	++	Data usually contained in LFS High level of data detail and reliability needed according to the OECD definition Broadening the definition makes calculation possible in most settings	Provides useful additional insights into the matching of skills to occupations. Easy to interpret
Empirical method	+	0	Requires detailed microdata to calculate Depends on good identification of (relevant) qualification levels	Difficult for cross-country comparison Difficult to calculate and interpret also in national context without detailed analysis
Beveridge curve	+	0	Requires vacancy data (by skill)	Harder to interpret
Non-LFS indicators	++	0	Data source should be reliable and regular	Easy to interpret Harder to be used in comparative context

Note: (*) Recommendation for use in national mismatch analysis/comparative analysis: +++ highly recommended; ++ recommended; + somewhat recommended; 0 not recommended.

Source: Economix, ETF

Calculation of the Beveridge curve also proved somewhat difficult and we do not generally recommend it for cross-country comparisons. Comprehensive vacancy data is hard to come by in many countries, especially if educational requirements need to be included. The curves are sometimes hard to interpret and are highly dependent on the country context (a more dynamic labour market influences the number and quality of vacancies; in some countries, unemployment does not play a big role). From a pragmatic point of view, it is not easy to show this dynamic indicator, which already has three dimensions – vacancy rate, unemployment rate, and time – in a cross-country comparison. It might, however, be worth experimenting with data crawling or big data analysis, keeping in mind potential biases (vacancies are posted multiple times online, companies search strategically, e.g. they indicate that they are looking for higher qualifications or more people than they actually need to increase their chances of finding a better candidate).

Indicators calculated using non-LFS data are always useful as additional information. To become part of a monitoring system on skills mismatch they should be based on regularly collected data sources. Most are based on employers' surveys, vacancy surveys or skills surveys. These are all very important in gaining an insight into the functioning of the national labour market and can also be used to check insights that are based on LFS data. They often involve very straightforward questions on skills mismatch and are easy to interpret and analyse. However, it is quite unlikely that we will find surveys that have identical questions relating to skills mismatch and a comparable sample in all countries – therefore such indicators are not recommended for cross-country analysis.

Data availability was mixed. While labour force surveys in most countries contain enough detailed data to calculate the indicators used, more non-LFS-based data would have been helpful in assessing the usefulness of a structural collection of alternative, or more specialised, measures of skills mismatch. Here, the school-to-work transition surveys seem to be an especially important as would warrant a detailed and structural collection of data to investigate the mismatch occurring in the school-to-work transition on a temporary or structural basis. It would allow the countries to provide more detailed insights into the potential shortcomings of the education process in providing adequate and practical skills, or in providing an adequate number of graduates in particular fields. To be fair, it has to be acknowledged that many countries attempt to collect such data, sometimes in a non-systematic way. For our purposes, however, the diversity of approaches and the collection of often only one single item of data allowed only for background information, rather than feeding into a cross-country comparison.

Next to age, which identifies the difficult school-to-work transition, gender seems to be a crucial dimension to analyse. In many countries, both labour market participation and access seem to be very different for men and women. Understanding the degree, but also the causes and consequences might help in shaping the right policy response.

Calculation of the indicators should be accompanied by some level of analytical description of the labour market and the institutional circumstances, as many of the indicators can provide an insight into the possibility of mismatch without proving or determining the exact causes of the mismatch. In the context of the countries studied in this report, the indicators only observe the status identified by the LFS. However, as in many countries dual labour markets exist, the differences between regular employment versus irregular (or informal employment) also exist, which might not always be well reflected in the LFS.

An additional dimension that could be analysed would be regional aspects. In particular, countries with a strong divergence between rural and urban labour markets or countries with very differential and quite separate labour market regions can benefit from such a distinction. In this context, it should also be acknowledged that the most detailed analysis by education, age group and gender within regions is probably beyond the capabilities of a normal LFS sample.

Strong evidence for mismatch could be found in the pilot countries. High levels of unemployment, differences in unemployment by education level and over-education could be found in all countries. All countries experienced problematic school-to-work transitions that are likely to be caused by structural and institutional problems in the labour market as well as shortcomings in the educational system. VET-based training showed mixed success in overcoming this problem, as only in some countries the indicators prove easier matches of VET-based workers relative to non-VET graduates. It should be noted in this context, however, that the identification of VET remains problematic in the data. The indicators are also likely to suffer from the fact that VET training is only provided in very specific qualifications or occupations, both in fields and levels.

The interpretation of the skills mismatch should be sensitive enough to the country context, the structure of the economy and its outputs, demographic context and migration.

Recommendations

One of the key challenges of this project was working at arm's-length with microdata. Not having access to the microdata prevented the project team from using dimensions and categories which were deemed best to deeply analyse the relevant issues using existing data. Data protection and reliability issues are valid reasons for prohibiting the widespread publication of microdata. However, it is crucial for the analysis of the existing data and for the development of analytical capacity that researchers, ministries and similar institutions are allowed easy access to microdata to fully use the potential that exists already in the microdata. Allowing researchers from abroad to work with and analyse the data potentially allows the country to tap into the insights of a global research community. While the research cannot be directed, it often provides insights for the country and inspiration for more policy-related analysis both in methods and in proposed solutions. It is therefore strongly recommended that consideration is given to making it easier to access microdata and to make it more easily accessible to researchers worldwide.

The LFS has been the workhorse of the research. It is crucial as a reliable and up-to-date data source. In comparing a country's result with other countries it proved to be the only reliable source of labour market data that could easily be found and compared to other countries.

Countries should consider strengthening their data collection in several ways. In small countries in particular, the sample size remains small, often too small to allow analysis along several dimensions. One way of circumventing this would be to increase sampling. Another approach might be to merge the sample with administrative data (e.g. social insurance data, pension data, education administration data). This would allow additional background information to be fed in, and in addition would allow for accumulated information across several waves. This has been done most notably in Norway, but also in other Scandinavian countries, and in the Netherlands. However, this would involve several years of preparation and analysis as administrative data is not currently collected for these purposes.

From our experience in working on similar comparative projects, we would recommend taking the time to perform data scoping exercises. This would involve identifying not only the data sources, but also the level of detail that the data might provide along several dimensions, especially key dimensions. Having an understanding of the underlying unweighted number of observations helps to infer the reliability of the data with respect to the planned research questions. In our context, some countries had few observations in key groups, e.g. unemployed or young people, especially when splitting these up along other dimensions (education, age, gender). A scoping exercise with detailed information on the cell sizes of key dimensions helps to optimally determine age groups, for example, to include as many observations as possible.

Additional data sources should be developed further, especially those that tap into areas that are of key interest to the labour market. For example, this could entail developing and regularly updating data collections that have already been initiated by various organisations within or from outside of the country. The key goal should be to build up the capacity to continue running and developing such data collections in the country. In addition, data collections that take place within the Eurostat context could be developed nationally. These would ensure comparability across Europe. Examples are the Adult Education Survey (AES), Structure of Earnings Survey (SES), Continuing Vocational Training Survey (CVTS) but also the vacancy surveys.

One of the key lessons to be learned is that the data alone does not speak for itself. Without the national context, the national insights into potential reasons for specific outcomes, the interpretation of the indicators is rather meaningless. The indicators merely provide the first signal of an issue at hand; the underlying reasons, approaches to mitigate them and policy recommendations should be developed with good insights into the general context. Working alongside with national experts in collecting but also interpreting findings has been crucial in this project.

Cross-country comparisons still prove to be difficult within a particular education level. National education systems, though translated to international ISCED standards, are not always meaningful when interpreted. While their use is necessary for cross-country comparisons, a deeper insight into the education system and its intricacies is crucial in identifying the key issues. This concerns also ISCO. Using the international classifications is always a trade-off but comparability remains important in this type of exercise. While countries have taken already measures to harmonise their statistical products with international standards, in certain cases labour force surveys still need to be properly synchronised with new standards in ISCED and ISCO classifications.

Given that VET and non-VET disaggregation was found as unfeasible or unavailable in many cases, we recommend to ensuring better coverage of VET programmes in labour force surveys, other types of surveys or studies (e.g. employers' surveys, tracer studies, sectoral analyses) and in administrative data (education, job seekers, vacancy). Current data is not fully capable of demonstrating the effect of VET on students and graduates, such as their labour market outcomes. This is due to the fact that data is missing but also to the fact that there are several internal quality issues linked to VET.

A key distinction in the education field therefore is the use of vocational training. Better identification of when and how vocational training is used in the education process might help to understand what role a more work-based training might have in mitigating some problems, specifically in the school-to-work transition.

ACRONYMS

Cedefop	European Centre for the Development of Vocational Training
CVAR	Coefficient of variation
DGEAC	Directorate-General for Education and Culture (European Commission)
ETF	European Training Foundation
EU	European Union
ILO	International Labour Organisation
ISCED	International Standard Classification of Education
ISCO	International Standard Classification of Occupations
JRC	Joint Research Centre (European Commission)
LFS	Labour force survey
NEET	(Young people) not in education, employment or training
OECD	Organisation for Economic Cooperation and Development
PES	Public employment services
PIAAC	Programme for the International Assessment of Adult Competencies (OECD survey of adult skills)
PISA	Programme for International Student Assessment (OECD)
STEM	Science, technology, engineering and mathematics
STEP	Skills Toward Employment and Productivity (World Bank survey)
VET	Vocational education and training

GLOSSARY

Job	A set of tasks and duties performed, or meant to be performed, by one person, including for an employer or in self-employment.
Labour force survey	Labour force surveys (LFS) are national surveys designed to capture representative data about the labour market, usually following definitions and concepts based on those developed by the ILO. Within the EU, labour force surveys are conducted annually.
Labour market information	Any information concerning the size and composition of the labour market or any part of the labour market, the way it or any part of it functions, its problems, the opportunities which may be available to it, and the employment-related intentions or aspirations of those who are part of it.
Matching	Matching denotes approaches and actions that aim to increase the employability of the workforce and reduce skills shortages, including filling jobs with qualified job seekers.
Mismatch	An encompassing term referring to different types of skills gaps and imbalances such as over-education, under-education, over-qualification, under-qualification, over-skilling, skills shortages and surpluses, skills obsolescence and so forth. Skills mismatch can be both qualitative and quantitative, referring both to situations where a person does not meet the job requirements and where there is a shortage or surplus of persons with a specific skill. Skills mismatch can be identified at individual, employer, sector or economy level.
Occupation	An occupation is defined as a set of jobs whose main tasks and duties are characterised by a high degree of similarity. A person may be associated with an occupation through the main job currently held, a second job or a job previously held.
Qualification	A formal expression of the vocational or professional abilities of a worker which is recognised at international, national or sectoral levels. An official record (certificate, diploma) of achievement which recognises successful completion of education or training, or satisfactory performance in a test or examination.
Skill	A term often used with very different meanings. Skill is understood here as having the ability to carry out a specific activity, acquired through learning and practice, where skill is an overarching term which includes knowledge, competency and experience as well as the ability to apply these in order to complete tasks and solve work-related problems.
Skills gap	Used as a qualitative term to describe a situation in which the level of skills of the employee or a group of employees is lower than that required to perform the job adequately, or the type of skill does not match the job requirements.
Skills shortage	Used in this guide as a quantitative term to describe a situation in which certain skills are in short supply, for example where the number of job seekers with certain skills is insufficient to fill all available job vacancies.

Source: ETF/Cedefop/ILO (2016a/b/c)

LITERATURE

Allen J. and van der Velden, R., 'Educational mismatches versus skill mismatches: Effects on wages, job satisfaction, and on-the-job search', *Oxford Economic Papers,* Vol. 3, 2001, pp. 434–452.

Bartlett, W., *Skill mismatch, education systems, and labour markets in EU Neighbourhood Policy countries*, WP5/20, Search Working Papers, 2013.

Bauer, T.K., 'Educational mismatch and wages: A panel analysis', *Economics of Education Review*, Vol. 21, No 3, 2002, pp. 221–229.

Berg, I., *Education and jobs: The great training robbery*, Praeger, New York, 1970.

Cedefop (European Centre for the Development of Vocational Training), *Skills, qualifications and jobs in the EU: The making of a perfect match?*, Publications Office of the European Union, Luxembourg, 2015.

Dekker, R., de Grip A. and Heijke, H., 'The effects of training and overeducation on career mobility in a segmented labour market', *International Journal of Manpower*, Vol. 23, No 2, 2002, pp. 106–125.

Duncan, G. and Hoffman, S.D., 'The incidence and wage effects of overeducation', *Economics of Education Review*, Vol. 1, No 1, 1981, pp. 75–86.

Egypt – Labour force survey 2014, 2014.

Egypt – Labour force survey 2015, 2015.

ETF (European Training Foundation), 'Anticipating and matching demand and supply of skills in ETF partner countries', ETF position paper, ETF, Turin, 2012a (unpublished).

ETF (European Training Foundation), *Measuring mismatch in ETF partner countries: A methodological note*, ETF, Turin, 2012b.

ETF (European Training Foundation), *Key indicators on education, skills and employment 2018*, ETF, Turin, 2018.

ETF, Cedefop and ILO (European Training Foundation, European Centre for the Development of Vocational Training and International Labour Organisation), *The role of employment service providers: Guide to anticipating and matching skills and jobs*, Vol. 4, Publications Office of the European Union, Luxembourg, 2015.

ETF, Cedefop and ILO (European Training Foundation, European Centre for the Development of Vocational Training and International Labour Organisation), *Using labour market information: Guide to anticipating and matching skills and jobs*, Vol. 1, Publications Office of the European Union, Luxembourg, 2016a.

ETF, Cedefop and ILO (European Training Foundation, European Centre for the Development of Vocational Training and International Labour Organisation), *Developing skills foresights, scenarios and forecasts: Guide to anticipating and matching skills and jobs*, Vol. 2, Publications Office of the European Union, Luxembourg, 2016b.

ETF, Cedefop and ILO (European Training Foundation, European Centre for the Development of Vocational Training and International Labour Organisation), *Working at sectoral level: Guide to anticipating and matching skills and jobs*, Vol. 3, Publications Office of the European Union, Luxembourg, 2016c.

ETF, Cedefop and ILO (European Training Foundation, European Centre for the Development of Vocational Training and International Labour Organisation), *Carrying out tracer studies: Guide to anticipating and matching skills and jobs*, Vol. 6, Publications Office of the European Union, Luxembourg, 2016d.

ETF, Cedefop and ILO (European Training Foundation, European Centre for the Development of Vocational Training and International Labour Organisation), *Developing and running an establishment skills survey: Guide to anticipating and matching skills and jobs*, Vol. 5, Publications Office of the European Union, Luxembourg, 2017.

European Commission, *Analytical web note 07/2015: Measuring skills mismatch*, Publications Office of the European Union, Luxembourg, 2015.

Eurostat, *Statistical approaches to the measurement of skills*, Publications Office of the European Union, Luxembourg, 2016.

FES (Friedrich Ebert Foundation), 'Generation in transition: Youth study Georgia', FES, South Caucasus Regional Office, Tbilisi, 2016.

Green, F., McIntosh, S. and Vignoles, A., 'Overeducation and skills: Clarifying the concepts', *Discussion Paper*, 435, Centre for Economic Performance, 1999.

Green, F. and McIntosh, S., 'Is there a genuine under-utilization of skills amongst the overqualified?', *Applied Economics*, Vol. 39, Issue 4, 2007, pp. 427–439.

Groot, W. and Maassen van den Brink, H., 'Overeducation in the labor market: A meta-analysis', *Economics of Education Review*, Vol. 19, 2000, pp. 149–158.

Handley M.J., Valerio A. and Sanchez Puerta M., *Accounting for mismatch in low and middle income countries*, World Bank, Washington DC, 2016.

Hartog, J., 'Overeducation and earnings: Where are we, where should we go?' *Economics of Education Review*, Vol. 19, 2000, pp. 131–147.

Hartog, J. and Oosterbeek, H., 'Education, allocation and earnings in the Netherlands: Overschooling?' *Economics of Education Review*, Vol. 7, Issue 2, 1988, pp. 185–194.

Hersch, J., 'Education match and job match', *Review of Economics and Statistics*, Vol. 73, No 1, 1991, pp. 140–144.

JRC (European Commission Joint Research Centre), *Occupational mismatch in Europe: Understanding overeducation and overskilling for policy making*, Publications Office of the European Union, Luxembourg, 2014.

Lazear, E.P., 'Firm-specific human capital: A skill-weights approach', *Journal of Political Economy*, Vol. 117, No 5, 2009.

Levels, M., Van der Velden, R. and Allen, J., 'Educational mismatches and skills: New empirical tests of old hypotheses', *Oxford Economic Papers*, Vol. 66, Issue 4, 2014, pp. 959–982.

McGuinness, S., 'Overeducation in the labour market', *Journal of Economic Surveys*, Vol. 20, 2006, pp. 387–418.

McGuinness, S., Pouliakas, K. and Redmond, P., 'How useful is the concept of skills mismatch?', ILO background note for the International Conference on Jobs and Skills Mismatch, Geneva, 2017.

Mendes de Oliveira, M., Santos, M.C. and Kiker, B.F., 'The role of human capital and technological change in overeducation', *Economics of Education Review*, 19, 2000, pp. 199–206.

Mincer, J., *Schooling, experience, and earnings*, NBER Press, 1974.

Murthi, M. and Sondergaard, L., 'Skills, not just diplomas: The path for education reforms in ECA', *Europe and Central Asia Knowledge Brief*, Vol. 20, World Bank, Washington DC, 2010.

OAMDI (Open Access Micro Data Initiative), *Harmonised labour force surveys*, Version 1.0 of licensed data files, LFS 2014, Central Agency for Public Mobilisation and Statistics, Economic Research Forum, Egypt, 2017.

OAMDI (Open Access Micro Data Initiative), *Harmonised labour force surveys*, Version 1.0 of licensed data files, LFS 2015, Central Agency for Public Mobilisation and Statistics, Economic Research Forum, Egypt, 2018a.

OAMDI (Open Access Micro Data Initiative), *Harmonised labour force surveys*, Version 1.0 of licensed data files, LFS 2016, Central Agency for Public Mobilisation and Statistics, Economic Research Forum, Egypt, 2018b.

OECD (Organisation for Economic Cooperation and Development), *Indicators on employment protection: Update 2009*, OECD Publishing, Paris, 2009.

OECD (Organisation for Economic Cooperation and Development), *Education at a glance 2010: OECD indicators*, OECD Publishing, Paris, 2010. Last accessed 28 February 2019 at: www.oecd-ilibrary.org/docserver/eag-2010-en.pdf

OECD (Organisation for Economic Cooperation and Development, *Technical report of the OECD Survey of Adult Skills (PIAAC)*, OECD Publishing, Paris, 2013b.

OECD (Organisation for Economic Cooperation and Development), *Skills outlook: First results from the OECD Survey of Adult Skills*, Vol. 1, OECD Publishing, Paris, 2013c.

Quintini, G., 'Over-qualified or under-skilled: A review of existing literature', *OECD Social, Employment and Migration Working Papers*, No 121, OECD Publishing, Paris, 2011.

Sattinger, M., 'Assignment models of the distribution of earnings', *Journal of Economic Literature*, Vol. 31, No 2, 1993, pp. 851–880.

Sattinger, M., 'Qualitative mismatches', *Foundations and trends in microeconomics*, Vol. 8, Nos 1–2, 2012, pp. 1–168.

Sicherman, N., 'Overeducation in the labour market', *Journal of Labour Economics*, Vol. 9, Issue 2, 1991, pp. 101–122.

Sloane, P., 'Much ado about nothing? What does the overeducation literature really tell us?', in: Büchel, F., de Grip, A. and Mertens, A. (eds), *Over-education in Europe: Current issues in theory and policy*, Edward Elgar, Cheltenham, 2003.

Sloane, D.J., Battu, H.B. and Seaman, P., 'Overeducation, undereducation and the British labour market', *Applied Economics*, Vol. 31, Issue 11, 1999, pp. 1437–1453.

Sondergaard, L., *Skills, not just diplomas: Managing education for results in Eastern Europe and Central Asia*, World Bank, Washington DC, 2011.

Spence, M., 'Job market signalling', *Quarterly Journal of Economics*, Vol. 87, No 3, 1973, pp. 355–374.

UNICEF (United Nations Children's Fund), Student performance in Georgia according to the programme for international student assessment (PISA), UNICEF, 2014.

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